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INNOVATIONS IN POVERTY REDUCTION

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Enterprising Psychometrics and Poverty Reduction

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Foreword: Innovations in Poverty Reduction

This Series

The time has come for innovative social science to contribute more to poverty reduction. The 2015 Millennium Development Goals (MDGs) are at risk from the global financial crisis and climate change inertia.[1] There are calls for hitherto silent disciplines—work psychology being the leading example—to help translate this MDG "grand plan" into everyday human behavior.[2] Just as demand has risen noticeably, so too has psychology's supply.[3] For the first time since the 1940s, in fact, a critical mass of psychological research is now focused not simply on poverty per se but on its *reduction*.[4] Moreover, psychologists as a profession for the first time arguably[5] find themselves focusing in the same place as the policy-makers and other disciplines such as economics—on the enablement of "human capabilities".[6] Human capabilities, perhaps we might call them competencies, are the stock-in-trade of psychology as well as of other social sciences. They include, for instance, improved health and well-being, supportive classroom environments, the promotion of social inclusion, gender equity, decent work conditions, and environmental awareness.[7] According to capability theory, these behavioral freedoms are all key means by which poverty is reduced.

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[1]United Nations. (2012). *The millennium development goals report 2012*. New York, NY: United Nations.

[2]Easterly, W. (2006). *The white man's burden*. Harmondsworth, UK: Penguin.

[3]Carr, S. C., & Bandawe, C. R. (2011). Psychology applied to poverty. In P. Martin, F. Cheung, M. Kyrios, L. Littlefield, M. Knowles, J. M. Prieto, & J. B. Overmier (Eds.), *The International Association of Applied Psychology [IAAP] handbook of applied psychology* (pp. 639–662). Brisbane: Wiley-Blackwell.

[4]Carr, S. C. (2013). *Anti-poverty psychology*. New York: Springer.

[5]Carr, S. C. (2013). *Anti-poverty psychology*. New York: Springer.

[6]Sen, A. (1999). *Development as freedom*. Oxford, UK: Oxford University Press.

[7]Carr, S. C., & Sloan, T. S. (2003). *Poverty and psychology: from global perspective to local practice*. New York: Springer.

This series connects supply with demand. First, it features the very best *innovative* psychological research on poverty reduction and capability development. Second, it employs an innovative *format*, the SpringerBrief. This is because the research is *programmatic*—too big for a journal article, too new for an entire book, but tailor-made for a monograph. Third, it will build momentum in the nascent field of humanitarian work psychology, including poverty reduction and its links with development economics and related social sciences.

The audience for these briefs is twin-faceted. On the one hand, it will appeal to applied psychologists in health, education, community, and organizations as well as psychologists studying poverty reduction per se. On the other hand, it will also appeal to other disciplines seeking new tools and fresh perspectives in development studies and policy formation, particularly with regard to the primary Millennium Development Goal of halving global poverty by 2015. Included are economists both macro- and micro-level, scholars of business and management at a "meso-" (mezzanine) level, and educationalists in development studies, health and allied disciplines, sociology of development, social anthropology, international studies, and the politics/political science of development. The series will also chime with policy-makers in aid and development, including both not-for-profit multilaterals and for-profit multinationals who are increasingly interested in the poverty-reducing potential of corporate social responsibility.

This Brief

It is no coincidence that the World Bank's World Development Report for 2013 focuses on "jobs".[8] With 200 million people unemployed globally, the creation of jobs, and more importantly creating more opportunities for decent work, is shown to be a core driver of, rather than just a by-product or a consequence of, global development. Out of three billion people in remunerated employment, half of them work in jobs that are classed by the International Labor Organization (ILO) as vulnerable—meaning unsafe, uninsured, or earning less than $2 per day ("working poor"). Decent work—meaning jobs that meet people's aspirations for workplace dignity and job security with a living/able wage—can raise income, empower women, foster social inclusion, and reduce conflict. It sets in train a virtuous cycle in which learning on the job builds capacity and prosperity, which garners more decent work and much more.[9]

Perhaps, there is no clearer example of this particular antipoverty process than the development of enterprises. As the World Bank notes, firms such as Honda, Microsoft, Charoen Pokphand, and Tata have metaphorically, and in some cases literally, "started in garages".[10] Yet, in many lower-income settings, much enterprise development continues to be hamstrung by "an adverse investment environment – for

[8] World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

[9] World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

[10] World Bank. (2012). *World development report 2013: Jobs* (p. 12). Washington, DC: World Bank.

example, access to credit".[11] This Brief is about the application of psychological principles, specifically psychometrics, to reverse that particular exclusion. Certainly not every micro-entrepreneur expects or seriously aspires to grow their organization beyond "survivorship," to the level originally envisaged by some development agencies—and it was perhaps presumptuous to expect them to.[12] Yet, there are countless entrepreneurs in lower-income settings who do seriously aspire to take a buzzing micro-enterprise out of the informal sector and grow it into a more fully fledged business or service organization, with workforce complements and new jobs—decent jobs—to match. And there are many formal small businesses that continue to be held back and with a little additional capital could enjoy further growth. They will often have the talent, human capital, and background training to succeed in their personal, and familial, goals, but just lack the capital necessary to take the next step.

All that may be stopping them from growing their businesses are external obstacles, rather than character traits or ability deficits. These might be due to practical and social constraints, such as human factors that come into play when going to a local bank, for example. First, there is a need for some money, lent at a reasonable, not usurious moneylenders', rate from a local bank. Beyond the obvious, however, there may not be adequate records, or demonstrated cost-effectiveness in existing ones, for the bank employee to be convinced (and confident enough) to lend them the money. In the wake of the latest global "economic crisis," banks that could (in principle) lend the capital at a reasonable rate may have diminished desire to risk relatively low returns per capital investment.[13] Meanwhile, the applicants themselves may be overwhelmed at the prospect of having to find the requisite "documentation" to get an application going, only to have it stall later on. In the Northern Territory, for example, this kind of barrier, widely seen as "red tape," can be a major impediment to enterprise development.[14]

This Brief is about innovatively enabling confidence in self and others to build and encourage investment by and in the entrepreneur, thus enabling opportunities for enterprises, and decent jobs, to grow.

Somewhat surprisingly perhaps, the Brief builds on a traditional strength in applied psychology: psychometrics. Often stereotyped as being a tool for screening people "out," this team has found a way, in the current environment, to use psychometrics to help screen them "in." By giving banks a means to assess their applicants' potential to cultivate and transition funds into growth, they enable more information and confidence to take the risk, and lend the money. In the process, people get a chance. An opening appears where none would otherwise present. Of course there are a plethora of "other factors" that matter in enterprise development. These range from educational level and pre-existing levels of human capital to adequate training in financial literacy, political skills, the radius of trust, and a range of other

[11] World Bank. (2012). *World development report 2013: Jobs* (p. 12). Washington, DC: World Bank.

[12] Banerjee, A. V., & Duflo, E. (2011). *Poor economics: a radical rethinking of the way to fight global poverty*. New York: Public Affairs.

[13] Carr, S. C. (2013). *Anti-poverty psychology*. New York: Springer.

[14] Ivory, B. (2003). Poverty and enterprise. In S. C. Carr & T. S. Sloan (Eds.), *Poverty and psychology: from global perspective to local practice* (pp. 251–266). New York: Springer.

contextual variables.[15,16] Nevertheless, money matters. While access to credit may not be a sufficient condition for development out of poverty through enterprise, it is often, absolutely, *necessary*.

The approach taken in this Brief is innovative because it is socially responsible. It is innovative because it addresses a "missing middle" in enterprise development, between micro- and mainstream enterprise development.[17] It is innovative because it incorporates and integrates, empirically, algorithmically, and conceptually, both global *and* local processes—a "glocality".[18] And it is innovative because it breaks from the conventional "psychological" approach to enterprise development, in which personality traits have held the limelight.

Classical psychological research on enterprise development, in the psychological vein, was conducted by D. McClelland and colleagues, from India to Malaŵi.[19,20] Yet this early work, while arguably quite groundbreaking and innovative in its own right, also pinned a lot on "personality" rather than on person(s) by situation(s) interactions. Much of the earlier work was focused on Need for Achievement, or *n*Ach, which in fact was a need for individual achievement.

Such motives do not always fit very well with local contexts, which tend to stress values that are relatively communitarian.[21] Indeed a critical limitation in the sustainability of the original *n*Ach training interventions seems to have been its apparent insistence on a particular form of achievement aspiration, rather than a wider range of attributes more in keeping with local traditions, values, and social norms.[22] Contexts, in particular, such as in social relations and human factors like tradition and trust, were arguably underrespected—a fundamental, potentially fatal, attribution error.

Partly as a result of the apparent lack of generality in single traits like *n*Ach, research on entrepreneurship in the 1990s moved away from the personality of entrepreneurs to entrepreneurial business.[23] Since 2000, the pendulum has swung back again, partly perhaps because of an international revival in personality theory, toward the "right stuff" for entrepreneurs.[24] Studies today include wider constellations of traits beyond *n*Ach, for example, aptitudes like working memory capacity[25]

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15 Easterly, W. (2006). *The white man's burden*. Harmondsworth, UK: Penguin.

16 World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

17 Klinger, B. (2011). Enabling capacity in the 'missing middle:' expanding roles for psychometric tests. *The Industrial-Organizational Psychologist, 48*(3), 97–100.

18 Carr, S. C. (2004). *Globalisation and culture at work: exploring their combined glocality*. Boston, MA: Springer.

19 McClelland, D. (1961). *The achieving society*. Princeton, NJ: Van Nostrand.

20 McClelland, D. C. (1987). *Human motivation*. Cambridge, MA: Cambridge University Press.

21 Ivory, B. (2003). Poverty and enterprise. In S. C. Carr & T. S. Sloan (Eds.), *Poverty and psychology: from global perspective to local practice* (pp. 251–266). New York: Springer.

22 Carr, S. C. (2013). *Anti-poverty psychology*. New York: Springer.

23 Cromie, S. (2000). Assessing entrepreneurial inclinations: some approaches and empirical evidence. *European Journal of Work and Organizational Psychology, 9*(1), 7–30.

24 Baum, J. R., & Locke, E. A. (2004). The relationship of entrepreneurial traits, skill, and motivation to subsequent venture growth. *Journal of Applied Psychology, 89*(4), 587–598.

25 Baron, R. A., & Ward, T. B. (2004). *Expanding entrepreneurial cognition's toolbox: potential contributions from the field of cognitive science* (pp. 553–573). Winter: Entrepreneurship Theory and Practice.

and opportunity identification.[26] These coexist alongside motives like *n*Ach,[27] indicating the utility of delineating multi-trait "Entrepreneurial Orientations" in a diversity of lower-income enterprise development settings.[28]

Crucially, the empirical studies have included the moderating impact of environmental constraints, such as having access to credit,[29] on the degree to which the "right stuff" entrepreneurially can realistically make a difference.[30] With appropriate checks on the cultural competency of measures and constructs, these studies have indicated the potential for entrepreneurial orientation to lead, in time, to greater prosperity and to be helped along, in time, by it.[31] Reciprocity like this is theoretically one hallmark of the inherent capacity for people to realize their own potential, through their own agency.[32]

Broadly speaking, that is where this Brief comes in. It takes the MDG "grand plan" and brings it down to earth with a process for enabling decent work, by enabling access to credit. It is evidence-based, antipoverty, practical, and fresh.

Enterprise development can be enabled by innovative psychometrics. But there is another leading aspect to the brief: the potential synergy between (i) enterprise development and (ii) gender empowerment.[33] Years ago, a respected friend and colleague of mine remarked that poverty reduction was the greatest challenge that people face, apart perhaps from equal opportunity for women. That comment has stayed with me for many years. Today, we know that under the Millennium Development Goals and, in particular, MDG 3—Promote gender equality and empower women, there has been significant progress in gender empowerment.[34] In particular, with the partial exception of sub-Saharan Africa, there are many more

[26] Baron, R. A. (2006). *Opportunity recognition as pattern recognition: how entrepreneurs 'connect the dots' to identify new business opportunities* (pp. 104–119). February: Academy of Management Perspectives.

[27] Rauch, A., & Frese, M. (2007). Let's put the person back into entrepreneurship research: a meta-analysis on the relationship between business owners' personality traits, business creation and success. *European Journal of Work and Organizational Psychology, 16*(4), 353–385.

[28] Frese, M., Brantjes, A., & Hoorn, R. (2002). Psychological success factors of small scale businesses in Namibia: the roles of strategy process, entrepreneurial orientation and the environment. *Journal of Developmental Entrepreneurship. 7*(3), 259–282.

[29] De Mel, S., McKenzie, D., & Woodruff, C. (2008). Returns to capital in microenterprises: evidence from a field experiment. *The Quarterly Journal of Economics, 123*(4), 1329–1372.

[30] Easterly, W. (2006). *The white man's burden*. Harmondsworth, UK: Penguin.

[31] McKenzie, D. (2012). Quo Vadis interviews in practice – Demand. In S. C. Carr, M. MacLachlan, & A. Furnham (Eds.), *Humanitarian work psychology* (pp. 182–200). Basingstoke, UK: Palgrave-Macmillan.

[32] Sen, A. (1999). *Development as freedom*. Oxford, UK: Oxford University Press.

[33] Schein, V. E. (2012). Women, work and poverty: reflections on research for social change. In S. C. Carr, M. MacLachlan, & A. Furnham (Eds.), *Humanitarian work psychology* (pp. 249–265). Basingstoke, UK: Palgrave- Macmillan.

[34] United Nations. (2012). *The millennium development goals report 2012*. New York, NY: United Nations.

girls today in primary school enrolments than in 1990, quite close in fact to being at "universal" levels.[35]

These gains notwithstanding, returns to education grow exponentially with level of education, from primary and secondary to tertiary education and training.[36] The World Development Report for 2013 contains a reminder that workplaces, too, are places where people can continue to see their talents grow.[37] We know that a glass ceiling continues to block gender equity in boardrooms and community settings across organizations globally.[38] Beneath that floor lies another massive inequity, in jobs per se. Thus, "women are significantly underrepresented in waged employment in low- and low-middle-income countries, [even though they] are more likely than men to work for wages in middle-income countries".[39]

Many of the entrepreneurs in this brief are women that are building their enterprises in lower-income countries. Some of their stories are told in the Brief itself and are very moving and uplifting. Underlining their stories is a fundamental synergy between gender empowerment and poverty reduction, enabled by the world of work, through jobs and enterprise development.

Quo Vadis?

The paradox of personality, including competencies at work, is that it can never be the whole solution, and yet there cannot be a solution without recognizing its importance. One size never fits all. Context always matters. A challenge, and opportunity then, is (a) identifying which particular mix of attributes and experiences are fit for purpose in current sociocultural, socioeconomic, and sociopolitical environments; (b) giving people a tool to probe for them; (c) letting them get on with it; and (d) evaluating the outcomes, with continual feedback to all key stakeholders. Process is just as important as outcome. In the final analysis, this Brief is about both outcomes and a process for finding innovative uses for the tools that can build people's confidence in one another.[40] This includes both entrepreneur applicants and the psychology of the bank employees and managers who make the decisions about credit

[35] United Nations. (2012). *The millennium development goals report 2012*. New York, NY: United Nations.

[36] World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

[37] World Bank. (2012). *Enterprise surveys*. www.enterprisesurveys.org. Accessed Nov 2012.

[38] Banerjee, A. V., & Duflo, E. (2011). *Poor economics: a radical rethinking of the way to fight global poverty*. New York: Public Affairs.

[39] World Bank. (2012). *World development report 2013: Jobs* (p. 50). Washington, DC: World Bank.

[40] Carr, S. C. (2013). *Anti-poverty psychology*. New York: Springer.

lending, and extends to work-life spillover.[41] It includes formal evaluations of reactions, behavioral change, and organizational learning from the process.[42]

It seems to me that a suitable *next* step in the process, after prospective evaluations have been conducted, is to shine evermore light into best-practice training for entrepreneurs who have secured the credit and have bridged the gap with it. How are the next steps facilitated and supported? An apt domain for any such training is in the skills of people management. According to the World Bank, there is relatively little awareness among would-be entrepreneurs, in lower-income settings, concerning the importance and relevance of acquiring management expertise in people domains like sociopolitical skills.[43] At the same time, randomized controlled trials suggest that conventional management training to date has had limited impact on actual business growth, especially when pretraining baselines are lower.[44] Maybe there is a connection—and a need for more innovative training models and outreach to help break the cycle.

Of course the impact of any training depends on the quality of the training, including its alignment with people's aspirations, the quality of its content, and the people skills of the trainers.[45] A lot could depend on training "fit" with its own business and organizational environment. How many low-income country entrepreneurs with small to medium enterprises can afford conventional "consultancy rates" for training in people management skills? A rhetorical question, perhaps, but it is possible that we enhance the economy of scale by extending the training to group sessions, anchored in and aligned with real critical incidents, set locally, with affordable (group, local) rates. Perhaps it is now time to build confidence in the impact that good training can affordably have on enterprise expansion, into the missing middle.[46]

Stuart C. Carr

[41] World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

[42] Kirkpatrick, D. L., & Kirkpatric, J. D. (2006). *Evaluating training programs: the four levels* (3rd ed.). San Francisco, CA: Berrett-Koehler Publishers, Inc.

[43] World Bank. (2012). *World development report 2013: Jobs* (p. 116/7). Washington, DC: World Bank.

[44] World Bank. (2012). *World development report 2013: Jobs*. Washington, DC: World Bank.

[45] Aguinis, H., & Kraiger, K. (2009). Benefits of training and development for individuals and teams, organizations and society. *Annual Review of Psychology, 60*, 451–474.

[46] Frese, M. (2013, January). *Evidence-based management*. Division of Occupational Psychology Conference keynote address. Chester, UK: British Psychological Society Conference.

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Contents

Chapter 1
The Development Problem

Abstract There is a huge lost opportunity in emerging markets. Between 310 and 380 million of small business owners want loans, and could earn very high rates of return on that additional capital if they could get it. Banks have this capital available, and want to lend it out, particularly to small businesses since competition in that segment is low, unmet demand is high, and the interest rates that can be paid are very attractive. But the connection between the banks and entrepreneurs just isn't happening, because it is extremely difficult for banks to evaluate risk and know who to lend to. The entrepreneurs running these small businesses typically lack credit history and collateral. They don't have well-formatted trustable financial statements, and many of their transactions are with cash. So banks have no means to identify the high-potential, honest entrepreneurs. Lending to small businesses in advanced economies suffered this same problem, until the banks started evaluating and serving small business more like they serve the mass individual segment rather than treating them as mini-corporations. One of the key innovations was to use individual borrowing history of the owner to evaluate risk for the small business loan, applying quantitative credit scoring. This approach lead to a rapid expansion in profitable and sustainable small business lending, because it leveraged what information was available, and did it in a way that kept transaction costs low so that banks could make a large number of smaller loans to businesses. But what can be done in emerging markets, where credit bureaus lack the depth and breadth of coverage?

An entrepreneur walks into a bank and asks for a loan…

This is not the beginning of a joke; it is the beginning of economic growth. Or at least it should be. Entrepreneurs are the drivers of productivity growth, moving factors of production from low-return activities to higher-return activities in new and innovative ways. They start and grow the businesses that provide new jobs for workers and new opportunities for consumers. And typically, for their businesses to start up or to grow, entrepreneurs require capital.

In some cases, entrepreneurs already have the capital they require to start and grow their businesses. But this is not necessarily the case: Those who happen to

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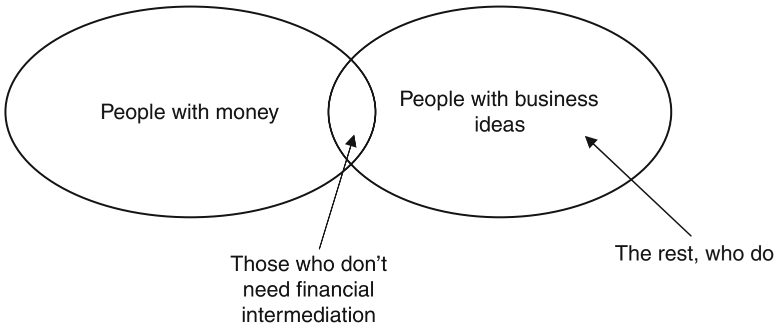

Fig. 1.1 An enterprise Venn diagram

have the productive business ideas out there in the world may not be the same people who happen to have the capital to carry them out. In any country, there is some distribution of business ideas out there, and there is also some distribution of capital. And for all those cases in a country where the distribution of money and the distribution of business potential do not overlap, financial intermediation is required to bring the two together.

The situation depicted in Fig. 1.1 is commonly the case in most of the world, but is especially so in lower-income settings, given the fewer number of people making up the first group and correspondingly smaller circle. In those countries, the need for productive intermediating capital is even greater.

Economies with restricted financial intermediation suffer through reduced entrepreneurship and economic growth. New business activities can only be started by those who have capital, which leads to certain symptoms of a lack of financial intermediation. For example, large conglomerates or family businesses that can cross-finance new activities with old seemingly unrelated ones are the only sources of innovation and new business growth.

Entrepreneurial finance is truly productive finance, as opposed to consumer finance. Consumer finance is typically used to shift consumption over time, the way a car loan allows you to get a car today with money you won't have until tomorrow. Other than the money spent on interest payments, the overall lifetime amount of wealth in that transaction is unchanged. Entrepreneurial finance is investment, deploying capital for workers, materials, and working capital, which when combined is meant to generate profit. When it is correctly deployed, the total amount of wealth over the lifetime increases for entrepreneurs, workers, and nations.

When most people in higher-income settings think of entrepreneurship, they think of high-tech start-ups conceived in a dorm room and transformed into Facebook or Google. And when they think of entrepreneurial finance, they think of the angel investors and venture capitalists that invest millions into these types of start-ups, and sometimes walk away with billions.

Though these may be the stories that get the attention, they are not the typical case. Even in the United States, let alone emerging markets, the vast majority of new businesses are involved in non-technology activities, started by adults with industry experience, and not generating exponential returns (Shane 2010). But even though their returns are small, their numbers are so large that they are the key piece of the aggregate economic picture and account for a major portion of employment and productivity growth.

Similarly, though bank lending is sometimes overshadowed by more exotic entrepreneurial finance provided by Angel and Venture Capital, commercial banks remain the lifeblood of business creation and growth around the world. Even in the United States, for example, Venture Capital firms finance less than 0.03 % of all new businesses founded in the country each year (Shane 2010). It is loans from commercial banks that are *the leading source* of external debt financing for new businesses in the United States (Shane 2010). Emerging markets have nowhere near the level of Venture Capital and Angel investor activity that is found in the United States, making commercial bank finance for entrepreneurship in those emerging markets only more important.

Are Banks Doing Their Job?

Though commercial banks are one of the largest sources of external capital for entrepreneurs in emerging markets, there is ample evidence that they are not coming close to meeting the needs of entrepreneurs, particularly those running small- and medium-sized enterprises in emerging markets. In this chapter, we will review that evidence and its consequences for economic growth. We will show how this unmet need is not necessarily due to malpractice on the part of the banks themselves but rather to the unique and significant challenges to finance small- and medium-sized enterprises, particularly in "developing" countries.

The simplest way to evaluate if the financing needs of small business entrepreneurs are being met by commercial banks is to ask them. The World Bank enterprise surveys (www.enterprisesurveys.org) do just that, surveying business owners and top managers of over 130,000 companies across 125 countries. And the results are striking. One third of firms identify access to finance as a major constraint to growth of their businesses. Globally, access to finance is rated as the single obstacle to business growth (16.2 %), beating out electricity costs/availability (14 %), informality (10.9 %), and tax rates (10.8 %).

Though telling, this is not conclusive evidence that banks are falling short in financing small- and medium-sized enterprises. Their owners may complain that they have difficulty accessing finance, but the banks may be right to deny them. Emerging markets suffer a host of problems that hurt small businesses' efficiency and profitability, such as high costs of formalization, poor infrastructure, and a lack of skills. If these problems mean that small businesses are excessively risky and not profitable, it is right that they should have difficulty accessing finance, because they do not represent good financial opportunities for lenders. It is possible that though small- and medium-sized enterprise owners want capital, they could not productively use it.

So how then can we truly tell if banks are meeting productive demand for entrepreneurial finance? In “Growth Diagnostics,” Hausman et al. (2005) introduce a powerful set of methodologies to move beyond symptoms to underdevelopment and to determine what may be the key binding constraints to economic growth. One of the cornerstones of this diagnostic methodology is that the absence of something good, like education or infrastructure or finance, does not necessarily mean it is preventing development. For example, low levels of education don’t necessarily mean that a lack of supply of education is preventing growth. The only way to determine if a lack of something is a binding constraint is to look at its shadow price. For example, if the scarcity of educated workers is harming development, then the price of those few educated workers that are available should be being “bid up” by firms in that country who desperately need their skills. In other words, it is not low educational attainment but high and rising returns to education that truly signal that education is being underprovided in a way that is restricting growth.

The same holds true for finance. It is not the absence of lending to small- and medium-sized enterprises itself, or owner’s desire for more loans expressed in surveys, that signals inefficient financial intermediation. Instead, we must look at the shadow price: the rates of return to capital. How much could small- and medium-sized enterprise owners earn with additional capital?

Most of the stories about constraints to small business growth suggest why these rates of return to capital are low. For example, excessive regulations, high taxes, or a lack of a “culture of entrepreneurship” mean that the average small- and medium-sized enterprises in the economy could not make productive use of additional capital. Such stories imply that small- and medium-sized businesses don’t have access, and indeed shouldn’t have access, to capital because their rates of return on that capital are low. Financial intermediation is only a problem if these rates of return to capital are high and going unexploited. That would mean that despite all the other challenges they face, small businesses could earn rates of return on extra money significantly higher than what it costs banks to provide it. This is the only clear evidence that there is economic inefficiency, and the provision of financial intermediation is a binding constraint to economic growth.

Returns to Capital Among Small Businesses

Measuring the return to additional capital among businesses is hard, because to do so accurately would require an exogenous increase in the amount of capital provided to them. That is, to know if increased lending would have high returns to capital, we have to externally increase the supply of lending to businesses and measure what happens. This is not an easy experiment to perform, since most lenders and investors only want to distribute their capital purposively.

Banerjee and Duflo (2002) take advantage of a natural experiment: a change in legislation in India. There, banks are required to lend a certain percentage of their portfolio to priority sectors, one of which is small-scale industry. In January 1998, the definition of this segment was expanded, meaning a host of firms that previously did not qualify were suddenly eligible and received a large increase in supply of lending due to this external change. Banerjee and Duflo found that a 1 % increase in lending lead to a 2.7 % increase in profit for these firms, representing "definite evidence of substantial under-lending" in India.

De Mel et al. (2008) go one step further. Instead of using a natural experiment to measure returns to capital, they performed a pure experiment and actually handed out gifts of capital to micro-enterprises in Sri Lanka in order to measure their returns to capital. These grants were the equivalent of approximately 20 % of invested capital in the businesses and were given to randomly selected business owners who were then closely followed, along with a control group. Again, the results show very high returns to capital. The randomly selected companies that received the grants earned in excess of 4 % per month profits on that additional capital.

What this evidence shows is that if small businesses could get more money, they could do a lot with it. Returns to capital are significantly higher than the cost of capital to banks—there are few countries where banks can earn 4 % per month returns. This divergence is the true indicator of insufficient financial intermediation constraining economic growth. Banks have money, small businesses need money, and those small businesses could earn more on that money than what it costs the bank to provide it. But the match is not being made, which is retarding economic progress.

There is an economic inefficiency in the provision of capital to small businesses. But how big is it? Is it a problem at the macroeconomic level, and is it a big opportunity for financial institutions? Stein et al. (2010) provide a mapping of the credit gap for small businesses, and though it is based on the same self-report enterprise surveys, their figures are truly impressive. They estimate that there are between 365 and 445 million micro-, small-, and medium-sized enterprises in emerging markets. Among those, they find that only 15 % can fully access the credit they need either externally or internally, leaving *310–380 million enterprises* that need more credit but can't access it. Their collective needs total *$2.1–$2.5 trillion US dollars.*

If we take only half of the 4 % per month return to capital figure from de Mel McKenzie and Woodruff, applied to an expansion of lending of $2.1 trillion, that would return more than 2.5 % of emerging market gross domestic product every year in additional incomes.

Why Don't Banks Lend More?

There are barriers in access to finance for small- and medium-sized enterprises in emerging markets, which is having a significant negative impact on employment and economic growth. But if small- and medium-sized enterprise owners could earn more on capital than banks could earn, why aren't banks lending more to those small- and medium-sized enterprises and pocketing the difference? Despite the recent credit crunch, banks remain well capitalized in most emerging markets.

Moreover, there is increased competition in traditional markets such as consumer and corporate lending, which is forcing banks to look for new sources of growth. So it is not clear why banks do not lend more to small- and medium-sized enterprises.

If you speak with the banks themselves, it becomes apparent that this relative lack of lending is not because they are not aware of the opportunity in small- and medium-sized enterprise lending. In a 2011 survey by the Inter-American Development Bank's Multilateral Investment Fund (FOMIN 2011, by its Spanish acronym) of 109 banks in Latin America and the Caribbean, 93 % considered small- and medium-sized enterprises as "strategic to their business," compared to 66 % in the previous 2008 survey. And 89 % of the banks surveyed had a specialized unit in their bank focused exclusively on small- and medium-sized enterprises lending, up from only 69 % in 2004 (FOMIN 2011).

However, banks also signal some specific challenges in lending to the small- and medium-sized enterprises segment related to risk. They have a difficult time assessing the risk of those seeking small- and medium-sized enterprises lending and selecting which entrepreneurs to lend to. The banks traditionally must bear higher transaction costs in this segment because of the difficulty in capturing information about risk and also suffer higher defaults compared to corporate or consumer lending. All this takes place against a background of recent economic crisis and uncertainty, which has further reduced banks' overall appetite for risk.

Why Small- and Medium-Sized Enterprise Lending is Different

When lending to consumers, banks assess risk by verifying the monthly income of the applicant—do they have a job with a regular income, and is that income sufficient to meet the consumer's other obligations plus the amount of the loan. Verifying this income can be done rather easily as long as the individual has formal employment, which has the benefit of formal and verifiable evidence such as pay stubs and employment tax records and which is relatively stable and predictable income over time. However, small businesses do not have a single regular paycheck. Their income can change significantly from month to month and can be difficult to verify, particularly in countries where many transactions are conducted in cash.

Larger businesses also have less regular income, but for larger businesses, there are more trustable records of sales transactions and a wider availability of well-formatted financial statements. Small businesses lack this information. The end result is that small businesses are more opaque than large businesses and salaried workers—banks have little information with which to evaluate risk.

Added to this is the issue of transaction costs. Large companies take out large loans, and a bank earns its money on the "spread" (difference between the interest paid on the loan and the cost of capital). Though spreads are smaller for lending to large corporations, these spreads are applied to significantly larger loan amounts as compared to small business loans, which means corporate lending can support much larger origination costs per loan. Sending skilled loan officers to spend weeks pouring over a large business's financial records and business plan is worthwhile for a $500,000 loan to a large corporate borrower. But the smaller loan amounts sought by small- and medium-sized enterprises cannot support very large transaction costs in loan origination, even if rates are higher: The spread is simply applied to too small a base. Hence loan officers cannot spend nearly as much time pouring over financial records, performing field visits, and gathering data for a loan of $15,000 compared to one of $150,000.

A Day in the Life of the Lender

Put yourself in the shoes of the manager of a large national bank in an emerging market economy. High-end commercial banking is frequently dominated by the largest (and often foreign) banks that can offer very sophisticated products and international services. In real estate lending and consumer lending, there is significant competition, as all of the banks have access to similar types of information. Everyone can verify pay stubs and value real estate to be pledged as collateral. But the small business market, by contrast, has less competition and price pressure. The massive segment of the economy running small businesses of varying degrees of formality is significantly underserved. Competition is low, but willingness to pay is high because these businesses have such high unexploited returns to capital that they can profitably borrow at reasonably high rates. Moreover, their current sources of financing are often informal moneylenders who charge exorbitant interest rates.

In addition to the high returns and low levels of competition, the small- and medium-sized enterprise (SME) segment has another attractive feature for you as a banker. Although the average level of risk is higher, the so-called fat tail risk of a broad and massive deterioration is smaller. For example, residential real estate lending typically features very low overall default levels. But when there is a crisis, losses skyrocket many standard deviations above the average. Though small businesses are also sensitive to macroeconomic conditions, they are less exposed than real estate and large corporations to this fat tail risk of a meltdown, making the sector attractive to banks from an overall portfolio management perspective.

So you want your bank to lend more to small- and medium-sized enterprises: But which ones to lend to? When a small-to-medium-enterprise owner walks in asking for a loan, you need to do a number of things. First, you need to simply verify their identity and that they are the actual owners of the business they are presenting. So you will ask for identity documents and probably registration documents for the business. Moreover, you need to get an idea of how well this business is doing and how much it would be able to repay in the future. So you need to ask the owner for information on their levels of sales, costs of rent, employees, supplies, and so on. And you need to make sure that the information they report is true, so you will want proof. But it will take you a long time to sift through mounds and mounts of original receipts to try and reconstruct the cash flows, a daunting prospect which would still require you to believe the truth of the underlying documentation, and potentially cost as much in salaries to your loan officers as the interest you would earn on the loan. So the transaction cost of those approaches make them a non-option. You could decide to go out and visit the business; to look for yourself at the levels of supplies, product stock, customer flows; and so on. But that takes a lot of time, and you might trust your own judgment but not the judgment of your newly hired loan officers.

This leaves you feeling uncertain about the past performance and current status of the business. And you still haven't evaluated the future possibilities of the business. This is what matters for your lending risk, because though it might have been successful in the past, it might not be able to continue that success into the future and continue to generate enough cash to make the loan payments. You can monitor for early signals of the loan deteriorating, like outstanding debts to other lenders, legal judgments against the business, and so on. But, at the end of the day, this information is very thin, and as the custodian of your client's deposits, you as a banker have to be responsible and avoid risk. So if you cannot evaluate the business' future potential, you can instead require the business to pledge collateral and/or a guarantor. That way, they have to make their own assessment of their future ability to service the loan, and if they are wrong in that assessment, it does not matter to you because you are still protected. Even if it is too expensive or not legally possible to seize the collateral, or impossible to liquidate it to cover your losses, the psychological effect in combination with the rest of the requirements listed above could be enough to cover your risks.

So you want to lend to small- and medium-sized enterprises, but the reality of the situation on the ground has required you to impose some very hefty requirements for documentation, collateral, and history. This may be cutting out many good small- and medium-sized enterprises from your client base, but it is the only way at your disposal to get down to a client pool that has a safe enough risk profile for you to protect your depositors and be profitable.

A Day in the Life of the Borrower

Now put yourselves in the shoes of the entrepreneur on the other side of this transaction. You are running a successful business, generating sizable cash inflows for you and your family. But your only source of money is retained earnings. This not only limits the amount of capital you have for bigger lumpy investments such as a new business location, vehicle, or machinery. Rather, even the lack of working capital itself causes you to leave profitable business opportunities on the table. For example, you can only purchase stock from resellers rather than importing your own containers from wholesalers in China, if you are running a clothing store, or you are unable to bid on a contract in a big office building for your janitorial business because you don't have enough working capital to cover the extra payroll that would be required during the initial weeks before the first payment comes in. The returns to capital are there, but you cannot take advantage of them.

There are probably informal moneylenders in your area. These aren't the stereotypical loan-shark mafia types as in the movies, but they are nonregulated, can resort to coercive and violent behavior to enforce payment, and worse of all for you, charge double-digit interest rates per month. You would be happy to pay double the highest interest rate the regular commercial banks are charging to most customers and could earn a hefty profit on it, so you go to the bank to ask for a loan.

You understand your business well and have all the figures clear. But the loan officer does not ask you for your description of the business and does not sit down with you to understand why you are such a good potential client. Instead, you are given a long list of required documents. First, your national identity card, which is easier, but then also the official registration form for your business, which you need to go order from the public registry office. That alone takes 10 days and has both an official and unofficial cost (i.e., a bribe) to obtain. The banker has also asked for financial statements. You have your registry of income and expenses that has been the backbone of your growing and successful business, but statements in a format that the bank wants is new to you and will definitely require time and the help of an external accountant to prepare. And even after all that, plus a visit to your shop, the bank is asking you for a guarantee—you need to pledge as collateral either a frozen deposit in a bank account or your home. If you do happen to own your own home, then you can use that, but that is another set of deeds and papers you need to go out and collect. And if you do not own your home, the bank will not accept your stock as collateral (they say it is too "mobile" to be used as collateral) nor your machinery (they say it is too "illiquid" to be used as collateral).

So at the end of the day, you are looking at weeks of running around to assemble all of the required paperwork, and that still does not guarantee you the loan, only that you can submit the application—it might be all for nothing, so much "red tape" (Ivory 2003). And the processing of the application can take weeks, during which time you'll lose the opportunity of importing that container or bidding on that janitorial contract. Things could be easier if you had collateral, but the only fast collateral is a frozen deposit—everything else requires an appraisal and lots of paperwork. Yes, that is right: To borrow money from them, you need to give them money as security. If you had the money, you wouldn't need the loan in the first place!

Towards a Solution: Evaluate the Individual

Even though this bank wants to lend and this business wants to borrow, and both are acting reasonably, there are two big challenges getting in the way. First, compared to other types of lending, there is less *information* available to evaluate the growth potential and risk of small- and medium-sized enterprises. Second, due to the smaller loan amounts, there are limits on the *ability* to gather more information. This is the main challenge in solving the sizeable and harmful problem of restricted small- and medium-sized enterprise finance: How can financial institutions evaluate risk for information-scarce small- and medium-sized enterprises with low transaction costs?

It is interesting to note that in the United States and other developed markets, these problems were also present and led to a relative restriction in small- and medium-sized enterprise finance that began to subside only relatively recently. Banks in the United States moved away from high-cost risk evaluation techniques for small- and medium-sized enterprises by local bank branches and towards low-cost automated techniques: credit scoring. Using credit scoring for small- and medium-sized enterprise lending only began in about 1993, but by 1998, 90 % of United States' banks had adopted it (Asch 2000). These automated scoring approaches led to a massive and highly productive increase in small- and medium-sized enterprise lending, because they solved the problem of high transaction costs. One of the main innovators, Wells Fargo, rose from the eleventh largest lender to United States small- and medium-sized enterprises to the second largest in only two years (Asch 2000), and the overall impact on the industry has been a "sea change" (Zuckerman 1996).

The key information behind these scoring models is not the small- and medium-sized enterprise's financial data, business plans, or other such information. The power of these models lies in their shift in focus away from the business and towards the individual business owner. The banks gave up trying to evaluate the small- and medium-sized enterprise like smaller versions of large-scale corporate borrowers and, instead, evaluated their risk based on the risk of the owner. For example, speaking of the very popular Fair Isaac's small business model,

> The models found that the most important indicators of small-business loan performance were characteristics of the business owner rather than the business itself. For example, the owner's credit history was more predictive than the net worth or profitability of the business (Mester 1997).

For small- and medium-sized enterprises, the individual at the center of the business is a key determinant of the success or failure of the enterprise, and therefore the risk associated with financing. Unfortunately this rich-country solution cannot be directly applied to emerging markets, because the long and detailed personal credit histories that are available in the United States are not available for most small business owners around the world. But it does point towards the key characteristics of a solution: It must have low transaction costs, be relatively automated to enable high-volume lending, and would benefit from focusing on the individual at the center of the business, rather than the business itself. In the following chapter, we will present a contribution that psychology can provide to this challenge, with potentially major impacts on small- and medium-sized enterprise finance and job growth in poor countries.

Chapter 2
A Psychology-Enabled Solution to Small- and Medium-Sized Enterprise Finance

Abstract Industrial and Organizational Psychology has developed tools to solve a similar problem: personnel selection. Big companies need to select among a large number of individuals applying for a job. This has to be done with relatively low transaction costs, and there is little information available to separate the good candidates from the bad candidates—a very similar problem to that facing the banks. Psychologists have developed psychometric tools to measure things like personality, motivation, outlook, and intelligence, which are related to subsequent job performance. These tools have been shown to work even better than other methods like interviews and background checks, and are widely used. What if they could be applied to the selection of small businesses to lend to? We review a variety of academic studies that have already used these tools to evaluate entrepreneurs and distinguish entrepreneurs from non-entrepreneurs and good entrepreneurs from bad entrepreneurs. The studies center on three main themes: personality, intelligence, and honesty. The first two relate to the ability to repay a loan, in that they could identify entrepreneurs who are more likely to successfully grow their business and its cash flows. Honesty relates to the willingness to repay a loan, as banks need to worry not just if the entrepreneur has enough money to repay but if they then decide to repay or else take the money and run. These studies provide initial insight into what particular characteristics and abilities could be systematically related to credit risk, and used for future lending to small business owners who would traditionally be rejected by banks due to a lack of information.

Industrial and organizational psychology has been working on a problem very similar to the challenge facing banks wanting to lend to small- and medium-sized enterprises in emerging markets. That problem is selection in human resources. Firms must decide which individuals to hire, based on little available information. Moreover, particularly for entry-level positions, firms must evaluate a large number of applicants in a low-cost way. To solve this problem of little information to evaluate individuals, and the inability to bear large transaction costs in that evaluation, is

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quite similar to the problem facing small- and medium-sized enterprise lenders in emerging markets. And to help solve this problem, industrial and organizational psychologists have developed a very large toolkit of tests. And it turns out that many of these tests have already been used to study the characteristics of successful entrepreneurs, finding a variety of robust relationships. These tools and results will be briefly reviewed here.

Psychometric Tools for Employment Selection

Personnel selection is a well-developed field in industrial and organizational psychology and is of immense economic importance to companies that must select and develop employees. Due to this importance, assessments for personnel selection have a long and deep history, going back a millennia, and evaluations of those assessments going back a century (Schmidt and Hunter 1998). This research has considered a variety of assessment types, including psychometric assessments of personality, integrity, and intellectual ability. Though there are debates, overall the results show a highly valuable contribution of these tools to the personnel selection process.

Schmidt and Hunter (1998) perform a major meta-analysis of these studies. Their results show that general intelligence tests, integrity tests, and personality tests are (along with work sample tests) the selection methods with the strongest ability to predict overall job performance. These tests beat out employment interviews, peer ratings, and reference checks, as well as biographical data, job experience, and level of education (which are also typically used in credit-scoring models). The relationships are statistically significant, particularly when they match the competencies required to do the job, and they are surprisingly persistent: Judge et al. (1999) show intelligence and personality are predictive of career success throughout one's entire professional life, until retirement, and even when measured at childhood.

Their perceived value is also evidenced by their widespread use by companies. According to a 2001 survey by the American Management Association, 41 % of employers test job applicants, including 20 % using cognitive ability tests and 13 % using personality tests (American Management Association 2001). A more recent survey found that between 2002 and 2007, the use of personality assessments for selection went from 21 % to 59 % of surveyed employers, the use of cognitive ability tests went from 26 % to 41 %, and the use of more general skills/knowledge tests went from 12 % to 56 % (Handler 2008). There are over 2,500 companies in the United States successfully developing and selling these psychometric tests for employee selection, and demand continues to rise.

Psychometric tools seem to be quite valuable then for personnel selection. Perhaps these same sets of tools could be applied to the evaluation of the quality of entrepreneurs and to boost confidence by banks to take a risk by lending to them. There is reason to believe so, as there is a long literature examining the psychometric characteristics of successful entrepreneurs, many using the same assessments that are applied to personnel selection.

Psychometric Studies of Entrepreneurship

There is a long history of research on entrepreneurs and entrepreneurship, including many studies examining how entrepreneurs differ from non-entrepreneurs or how good entrepreneurs differ from bad entrepreneurs. Much of this work uses psychometric assessments to try and measure these differences.

One of the earliest examples is D. McClelland's (1961) seminal work, suggesting that the psychological "need for achievement" *(or nAch)* is the key driver of entrepreneurial behavior among individuals. This was but the first of thousands of studies over the past 50 years examining what characteristics and traits are related to entrepreneurial outcomes. For a detailed review of this literature, see Chell (2008).

A valuable meta-analysis is provided by Rauch and Frese (2007). This study combined the results of 116 independent samples yielding a sample size of 26,700. The authors found consistent and moderate relationships between various psychometrically measured traits and entrepreneurial outcomes. Their desire to "put the person back into entrepreneurship research" is not without its skeptics, who view the trait approach to the study of entrepreneurship as flawed (e.g., Gartner 1989; Shaver 1995). The majority of these studies examine either the likelihood of business creation (in other words, the differences between entrepreneurs and non-entrepreneurs) or the likelihood of business success (in other words, the differences between good entrepreneurs and bad entrepreneurs). It is difficult to specify the outcome variable and comparison groups in these studies, which is a major shortcoming in the literature (Shaver 2007). As will be discussed further below, this is one of the advantages of the present study, which has very clear and cleanly defined outcome variables and comparison groups: defaulters versus non-defaulters and high-profit versus low-profit small business owners.

For the present study, we will focus on psychometric assessments across three broad themes that have established findings in both the personnel selection and entrepreneurship literature: personality, integrity, and intelligence.

Personality

Distinguishing personality characteristics of entrepreneurs are the most traditionally studied of these three themes, going back to the work of McClelland (1961). The same holds true for descriptions of the distinguishing characteristics of successful entrepreneurs in the popular press and society in general. When talking about how entrepreneurs are different, the most commonly heard characteristics relate to personality, such as differences in drive, motivation, creativity, persistence, and risk taking. In the study of personality, the five-factor or "Big Five" personality model of Openness to new experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism/emotional stability (Barrick and Mount 1991) is the dominant model, and it has been used in the study of entrepreneurs in a number of works.

Holland (1985) described an Entrepreneurial type (E-type) in his RIASEC vocational personality model (In Holland's model, the acrostic "RIASEC" stands for Realistic, Investigative, Artistic, Social, Enterprising and Conventional). This is a typology, meaning that not all E-types become successful entrepreneurs, yet the E-type traits will be displayed by most entrepreneurs. In the Big Five model (above), this E-type has been related to higher Conscientiousness and Extraversion and lower Agreeableness and Neuroticism, without differences in Openness (Gottfredson et al. 1993).

The empirical work on entrepreneurship and the Big Five is most completely reviewed in Zhao and Seibert (2006), who perform a systematic meta-analysis on the Big Five and entrepreneurial status. Entrepreneurial status is the selection of an individual into an entrepreneurial career, typically as opposed to a management career. The factors related to selection into entrepreneurship could be quite different from those related to success once one has engaged in an entrepreneurial venture. However, the studies examined in this meta-analysis test current entrepreneurs against managers, and therefore the pool of entrepreneurs has at least achieved sufficient success in entrepreneurship in order to start a venture and survive long enough to be tested the study. Therefore, entrepreneurial selection necessarily includes at least some element of success in entrepreneurship.

Zhao and Seibert (2006) provide both literature review and arguments to advance the following hypothesized relationships: Entrepreneurs will score lower than managers on Neuroticism and Agreeableness. Entrepreneurs will score higher than managers on Extraversion, Openness, and Conscientiousness, and within Conscientiousness, both achievement motivation and dependability will be higher for entrepreneurs than managers, but potentially to different degrees.

The results of Zhao and Seibert (2006)'s meta-analysis found support for the hypothesis that entrepreneurs scored lower than managers on Neuroticism and Agreeableness and that entrepreneurs scored higher than managers on Openness and Conscientiousness (which had the largest effect). There was not conclusive evidence on differences in the relationship of Extraversion to entrepreneurial status (defined as the probability of being the founder, owner, and manager of a small business whose principal purpose is growth, as opposed to a salaried manager in a business). Within Conscientiousness domain, the authors found that the sub-facet with the strongest relationship to entrepreneurial status is *n*Ach. Entrepreneurs had significantly higher *n*Ach than managers, but both groups were indistinguishable in terms of the dependability sub-facet in the Conscientiousness domain. Interestingly, the authors also considered the hypothesis that the relationships of two of the Big Five (Neuroticism and achievement motivation) were moderated by national cultural dimensions of uncertainty avoidance (need for structure, certainty, rules) and performance orientation, respectively, but found no supporting evidence for this hypothesis, supporting the possibility that these tools could be used for selection across different cultures or at least the range of cultures sampled in the literature that was reviewed in the meta-analysis.

In addition to examining the direction of the relationship with individual traits, Zhao and Seibert (2006) examined the overall predictive power of the Big Five personality traits to entrepreneurial status and found an adjusted R-squared of 0.37. This is moderate in the social sciences when attempting to fully explain phenomenon, but in terms of predictive power typically used for selection and credit scoring, this is a relatively strong result, explaining a portion of the variance that could allow for major risk splitting power if anything near this R-squared could be achieved in predicting default.

This highlights one of the weaknesses of the bulk of studies on entrepreneurship and personality that Zhao and Seibert review: the focus on selection into entrepreneurship rather than success at entrepreneurship. They are somewhat related, but from the point of view of resolving the barriers in small- and medium-sized enterprise access to finance highlighted above, we must extend these results to more appropriate prospective rather than concurrent outcomes.

Ciavarella et al. (2004) take one step further in this prospective direction by examining long-term venture survival rather than entrepreneurial status at various stages as in the literature reviewed by Zhao and Seibert (2006). Ciavarella et al. (2004) examine both the probability that the entrepreneurial venture will survive for at least 8 years, as well as the overall lifespan of the entrepreneurial venture, as their outcome variables, within a sample of United States college students followed over the span of their careers. Their hypothesized relationships are that Extraversion, Agreeableness, Conscientiousness, and Openness will be positively related to venture survival while Neuroticism will be negatively related. Interestingly, their hypothesis on the relationship with Agreeableness is in the opposite direction of that in Zhao and Seibert (2006) and Holland's E-type (1985). The authors argue for this relationship based on the link between Agreeableness and ability to cooperate effectively (Judge et al. 1999) which in turn has been listed as a key factor in entrepreneurs' ability to secure capital (Cable and Shane 1997) and partner with suppliers.

The results of Ciavarella et al. (2004) found support for the positive relationship between Conscientiousness and venture survival and found a weakly negative relationship between Openness and venture survival. The other Big Five traits did not have significant relationships with venture survival. It is important to note however that the study had a small sample size compared to Zhao and Seibert (2006), with only 111 entrepreneurs.

Ciaverella et al. (2004) suggest that one of the reasons for the negative relationship with openness (that contradicts prior studies) may be that those with higher openness are more likely to select into entrepreneurial careers but conditional on that, may be less likely to succeed, highlighting the need for better outcome variables in the study of entrepreneurial *outcomes*. The authors call for this explicitly: "further studies should examine the effects of the Big Five personality variables on other measures of performance, such as sales and/or employee growth, profitability measures, and effects on stakeholders" (p. 481).

For similar reasons as those used by these authors, we use a personality assessment based on the five-factor model, provided by a leading test provider for professional industrial and organizational psychologists.

Intelligence

Popular literature on entrepreneurs typically refers to psychological characteristics such as drive, motivation, and risk taking but does not as often comment on intelligence. Success in entrepreneurship is not necessarily correlated with academic achievement, as evidenced by high-profile university dropouts like Mark Zuckerberg and Bill Gates, though more systematic studies of the subject do find links between education and entrepreneurial outcomes (De Mel et al. 2008). Educational attainment though is not necessarily related to intelligence, particularly in emerging markets where access to education can be driven largely by socioeconomic status. We therefore examine both educational attainment and two popular tests of intelligence.

The first test is of digit span recall, a component of the Wechsler Adult Intelligence Scale (WAIS-III), probably the most widely used intelligence test worldwide. The test taker is shown a string of digits for 5 s, the string is then hidden for 5 s, and then the test taker must enter the number. If they do so correctly, the subsequent number is one digit longer, and the test continues until a mistake is made. The same is then repeated, but the test taker must enter the number in reverse.

Economists studying the links between individual-level differences and entrepreneurial outcomes have been using the digit span recall test with increasing regularity, first Djankov et al. (2005), who found that in a random survey of Russian entrepreneurs and non-entrepreneurs, entrepreneurs scored significantly higher on the digit span recall test, and this was one of the strongest individual-level differences between the two groups. This finding was subsequently repeated in Brazil (Djankov et al. 2007) but was not found to hold in the People's Republic of China (Djankov et al. 2007).

The same digit span recall exercise was subsequently used by De Mel et al. (2008) in the previously mentioned returns to capital experiment. In that experiment as we saw above, the authors found very high returns to capital for randomly-selected entrepreneurs, 5.7 % per month on average (68 % per year). Moreover, they found that these returns varied between individuals to the greatest degree by intelligence. Those that scored only 4 on the digit span recall test (bottom 15 %) had negative returns to capital, while the median scorers (6 digits) earned on average 4.8 % per month and those who scored 8 or more (top 11 % of test takers) had returns of 13.6 % per month. Such a test could therefore potentially serve as one indicator to help identify higher-potential entrepreneurs.

Digit span recall tests attention and recall but is not often used alone as a test of the broader construct of "intelligence." We therefore apply an additional test, the Ravens Progressive Matrices. This classic nonverbal test contains matrices of incomplete visual patterns, along with eight potential answers to correctly complete the pattern. This test has traditionally been considered to be "perhaps the best of all nonverbal tests" of general intelligence by Charles Spearman (1946), the creator of the construct. Recent evidence suggests that there may be an additional component of spatial/perceptual processing tested by the matrices, beyond generalized intelligence (Schweizer et al. 2007). Nonetheless, this test remains one of the oldest and most frequently used in the literature.

The Ravens Progressive Matrices have been used by other entrepreneurship researchers alongside the digit span recall test. For example, De Mel et al. (2010) conducting their research in Sri Lanka found that these two measures help to strongly distinguish entrepreneurs from waged workers. Moreover, the authors show that ability as measured by these two assessments can be used to distinguish what proportion of own-account (i.e., self-employed) workers are small- and medium-sized enterprise entrepreneurs whose businesses have yet to grow versus those that are self-employed out of necessity due to a lack of jobs and are more like salaried employees-in-waiting rather than entrepreneurs.

Continuing from these results, we deploy Ravens Progressive Matrices as a second test of intelligence alongside the digit span recall test. Ravens Progressive Matrices are used with permission from test owner Pearson Assessments.

Integrity

When speaking of lending, two drivers of risk are often distinguished: ability to pay and willingness to pay. The former refers to whether or not the borrower has enough cash to repay the loan—if they are ineffective entrepreneurs and their business does not generate enough cash to repay the loan, they will have to default or restructure the debt. However, there is also the risk that the borrower has sufficient cash to repay the loan but still chooses not to. This is known as strategic default, discussed frequently in the mortgage borrowing market after the 2008 financial crisis.

Past cash flows are difficult to establish and future cash flows are difficult to predict for small- and medium-sized enterprises. Therefore, psychometric measures that relate to entrepreneurial ability could clearly help predict entrepreneurs' future ability to generate cash flows from their business to repay loans, that is, their ability to repay. Yet psychometric instruments could *also* evaluate the other driver of risk, willingness to repay, through evaluations of honesty and integrity.

Honesty and integrity testing is very important in human resource contexts as well, where firms are keenly focused on losses due to employee theft and unethical behavior. This need has led industrial and organizational psychologists to develop a number of assessments of honesty and integrity. One such instrument was evaluated by Bernardin and Cooke (1993), who showed that an integrity assessment taken at the time of application for entry-level staff at a convenience store was a strong predictor of who was subsequently fired for on the job theft, explaining over 10 % of the variance. In general, integrity tests have been shown to relate to job performance, though recently a debate has emerged as to the strength of this relationship, as many impact studies are written by test vendors using unpublished data, rather than appearing in peer-reviewed journals (Van Iddekinge et al. 2012). Restricting attention only to the most rigorous of evaluations continues to show a relationship, though more moderate in strength.

While the relationship between integrity and job performance is established, the relationship between integrity and entrepreneurial outcomes has not yet been systematically evaluated. Indeed, even the expected direction of the relationship is not intuitively clear. Are dishonest entrepreneurs more likely to fail at business because they cannot generate the trust needed for relationships? Or are honest entrepreneurs more likely to fail because they will be taken advantage of in the cut-throat marketplace? The theoretical relationship between integrity and entrepreneurial success could be in either direction.

To measure these relationships, we use an assessment that is a direct descendent of that used in the Bernardin and Cooke (1993) paper, which was shown to be predictive of which small business wageworkers were more likely to be subsequently fired from their jobs due to on-the-job theft. This assessment, originally written for wageworkers, was adapted to the context of small business owners.

Chapter 3
Methodology

Abstract We took a set of the psychometric instruments reviewed in Chap. 2 and gave them to a sample of 1,580 small business owners. The majority of businesses had 0–5 employees, had been in operation for more than 3 years, and had $10,000 USD or less in monthly sales. The sample had nearly an equal mix of males and females, typically between the ages of 25 and 54, and over three quarters had at least completed high-school studies. These entrepreneurs were selected because they had loans at one of six participating banks and microfinance institutions across Peru, Kenya, Colombia, and South Africa. Most loans were between $800 and $3,000, though the banks in Kenya & South Africa included clients with loans from $20,000 up to $100,000. Each client was given the series of assessments by representatives of the financial institution. The clients already had their loans for at least six months, and therefore the clients knew that their answers would not directly impact their loan (i.e. a low-stakes setting). This is useful for research, though not ideal for implementation as psychometric tools for credit scoring would be used in practice in a high-stakes setting, where applicants will try to manipulate their responses to get approval of their loan application. In evaluating the contribution of psychometric instruments to better identify high-potential entrepreneurs and direct finance to their ventures, there are two principal outcomes of interest: Business performance (best represented with company profits); and loan repayment (i.e., did the person default). We collected loan repayment history from the financial institution, and profit levels as reported by the entrepreneurs, to compare to responses on the psychometric assessments.

Empirical Strategy: Design Overview

The results reviewed in the previous chapter suggest that there are some dimensions measurable with psychometric instruments that have, at least in some cases, important relationships with entrepreneurial outcomes. However, as noted in many

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reviews of this body of literature, there are shortcomings with the studies. Many times, the entrepreneurial outcomes that are available for study are not ideal. For example, the studies may only know if the individual is self-employed or not but do not have data on how well the individual's business is actually doing. In this study, we benefit from well-defined measures of business and loan performance.

Another key challenge is that the samples typically available for such studies are drawn for convenience's sake. See, for example, the large number of samples drawing on classes of graduate students in developed countries, to whom researchers have easy access. As noted in a recent special issue of the *Journal of Economic Psychology* focused on the entrepreneurial personality research, "the papers in the special issue also make clear that to answer these questions, more data are needed," and moreover, "once we have such data- whether the results we find for industrialized countries can be extrapolated to transition economies and developing countries" (Caliendo and Kritikos 2012). The need for more data and data drawn from emerging markets is a key contribution of this work.

Most importantly for the question as to whether or not such instruments could increase access to finance, none of these past studies have directly examined loan repayment. In the present study, we will have the benefit of clearly defined outcome variables including loan repayment itself, as well as a highly relevant sample to the question of increasing access to finance: samples of existing small business borrowers from multiple emerging markets.

How can we figure out if we can use psychometric tests to distinguish high-risk from low-risk entrepreneurs in a meaningful way?

If we were interested in precisely estimating the causal relationship between psychometric characteristics and entrepreneurial outcomes, we would have to actually change these characteristics among a randomly selected treatment group and compare them to a control group. In other words, exogenously change intelligence or personality and observe the impact on entrepreneurial outcomes. This is not possible, as the types of traits measured by these tests like personality and intelligence are the outcome of a long process of influences, even genetic factors. They typically do not change much once an individual reaches adulthood (Costa and McCrae 1994), and even if they do, interventions to alter personality are neither well established nor feasible in most research setups.

So randomly varying the traits is not possible. But, in the case of examining psychology's potential contribution to unlocking access to finance, we are not really interested in isolating causal relationships. Many inputs into traditional credit scoring models like an address are not chosen because they necessarily have a causal impact on risk but simply because they have a correlation that can provide predictive power. Similarly, much of the research in industrial and organizational psychology for personnel selection is concerned exclusively with predictive validity, not causality (Almlund et al. 2011). Analogously, we are interested in evaluating tools for screening applicants for finance and identifying high-potential entrepreneurs. Other methods of doing this use proxies, such as the number of dependents, and to test whether these can be replaced with psychometric tools, we must simply examine the power and stability of the relationship between the dimensions we can measure with psychometric instruments and the outcomes we want to predict.

At a first approximation, the psychometric dimensions we seek to measure are stable over time among adults. This allows us to measure them and compare to historical and concurrent outcomes. Therefore, the approach taken herein is to apply psychometric measurements and compare them to current business characteristics and recent loan repayment performance.

This approach does face a number of challenges. Responses to the self-reported psychometric questions used here could be biased, with the respondents attempting to give more socially desirable answers. In this case, clients were explicitly told that their responses would have no effect on their relationship with the financial institution, reducing their desire to give socially desirable responses. Moreover, Hough et al. (1990) and Hogan (1991) show that even in high-stakes settings, respondents rarely manipulate their answers to these types of psychometric assessments unless explicitly instructed to do so.

In actuality, the bigger problem may in fact be the exact opposite: Clients may not manipulate their answers enough. The ultimate goal is to evaluate the potential for these types of tests to be used as screening devices to allocate finance and assistance to entrepreneurs. This means that when entrepreneurs complete the psychometric assessments, they would be under high incentives to give socially desirable answers and "game" the test. To determine if these types of psychometric questions can be implemented in such a high-stakes setting, it would be desirable to replicate that high-stakes situation as closely as possible. In the case of intelligence and skills, there is less of a concern of faking for social desirability because it is not possible to fake on such questions. However, there is an impact of effort on such tests because complex thinking is not automatic and requires effort (Schmeichel et al. 2003), and this "low-stakes" situation may reduce effort and therefore affect results of those questions.

A cleaner method than testing entrepreneurs in a low-stakes setting and looking at their history would be to test the entrepreneurs in a "high-stakes" setting to mimic the incentives in place if the tool were implemented and then to follow them subsequently to address the potential for reverse causality. Such high-stakes up-front testing will be pursued in future studies but has the drawback that a great deal of time must pass between testing, providing financing and then having loans mature and business performance unfold. Testing applicants and looking at current business performance and loan repayment history, while not perfect, has the advantage of providing information more rapidly. Moreover, the comparative results across the dimensions investigated here still contain valuable information because the incentives and timeframe are consistent across the entire sample. For example, all participants have the same motivation in their performance of the Ravens Progressive Matrices and digit span recall tasks, meeting what is termed "standardization for effort" (Almlund et al. 2011).

Testing concurrently to measuring outcomes also limits the types of psychological and cognitive dimensions that can be considered, in favor of the most stable. But for future work, we could extend the focus beyond the more stable dimensions like intelligence and personality and also examine more variable/malleable psychometric dimensions. These dimensions could be tested, and even combined with interventions to improve them in a targeted way. Moreover, this testing and targeted training around malleable dimensions would allow for closer evaluation of causal relationships between the dimensions and outcomes of interest, because randomly selected participants could have the dimensions altered with the training. See Glaub et al. (forthcoming) for a study using this methodology: a randomized control trial of personal initiative training program on entrepreneurs in Africa.

High-stakes ex ante testing and inclusion of stable and malleable traits will be pursued in future research. However as a first examination, testing in a low-stakes situation and comparing responses to historical data is still quite revealing, particularly since the outcome variable and sample available for the present study is a major improvement over what is available in much of the literature to date.

Sample

To evaluate the potential contribution of psychometric tools to entrepreneurial evaluation, we partnered with six financial institutions in four countries:

- Bank #1: A small microfinance organization in semi-urban and rural Peru with average loans of $2,000 to $3,000
- Bank #2: A large commercial bank in Kenya providing with average loan size of $2,000
- Bank #3: A large microfinance organization in Colombia with an average loan size of $800
- Bank #4: A very large commercial bank in South Africa providing loans of $20,000 to $100,000
- Bank #5: A medium-sized commercial bank in Kenya providing loans from $5,000 to 25,000
- Bank #6: A large microfinance organization in Lima, Peru, with an average loan size of $1,000

Following are some summary statistics of the sample.

The majority of entrepreneurs tested were between the ages of 25 and 45 (Fig. 3.1, Table 3.1). The overall sample has a larger number of female than male entrepreneurs, though it can be clearly seen that this is due to the large percentage of female clients of the smaller, Latin American micro-lending institutions (Fig. 3.2, Table 3.2). Microfinance institutions traditionally target female borrowers as they are viewed as lower credit risks and are frequently engaged in small-scale business activities lacking in access to credit, but as finance sizes grow, the gender breakdown of clients begins to skew more heavily towards male borrowers. This concentration of female borrowers only in lower sizes of finance is increasingly being called the female “microfinance ghetto.” In terms of education level, the majority of respondents have at least secondary education, with 40 % having post-secondary training of some type (Fig. 3.3, Table 3.3).

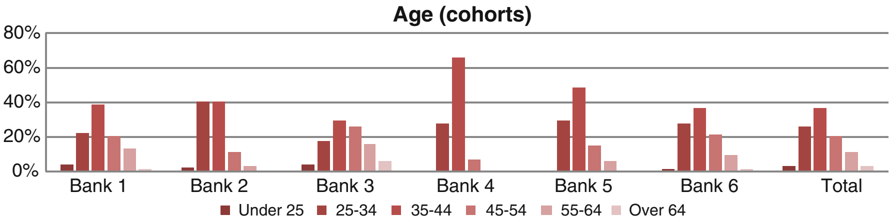

Fig. 3.1 Age distribution by bank in the sample

Table 3.1 Age distribution by bank in the sample

	Partner						
Age (cohorts)	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
Under 25	4	3	4	0	0	2	3
25–34	23	40	18	28	30	27	26
35–44	38	41	30	66	49	37	37
45–54	20	11	26	7	15	22	20
55–64	13	4	16	0	6	10	11
Over 64	1	1	6	0	0	2	3
Total	100	100	100	100	100	100	100

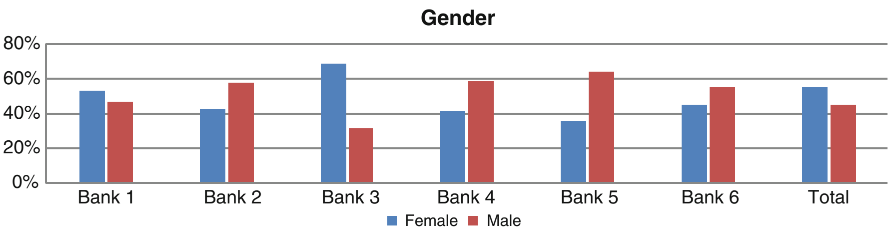

Fig. 3.2 Gender composition by site

Table 3.2 Gender composition by site

	Partner						
Gender	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
Female	53	43	68	41	36	45	55
Male	47	57	32	59	64	55	45
Total	100	100	100	100	100	100	100

In terms of the businesses themselves, business size unsurprisingly relates closely to the size of financing offered by the financial institution (Fig. 3.4, Table 3.4). Over half the sample consists of businesses earning $1,000 or less per month in sales revenues and 90 % earning less than $120,000 per annum with 5 or fewer employees

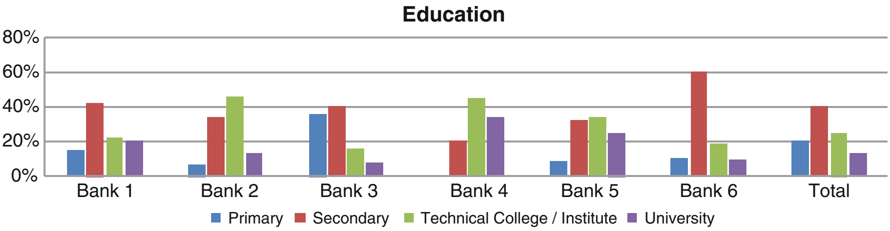

Fig. 3.3 Education in the sample

Table 3.3 Education in the sample

	Partner						
Education	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
Primary	15	7	36	0	9	11	21
Secondary	42	34	40	21	32	61	40
Technical college/ institute	22	46	16	45	34	19	26
University	21	13	8	34	26	10	13
Total	100	100	100	100	100	100	100

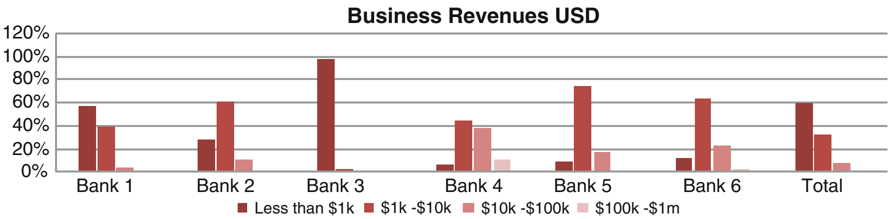

Fig. 3.4 Business revenue in the sample

Table 3.4 Business revenue in the sample

	Partner						
Business revenues USD	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
Less than $1k	57	28	97	7	9	12	59
$1k–$10k	40	61	2	45	74	64	33
$10k–$100k	3	11	0	38	17	23	7
$100k–$1m	1	0	0	10	0	2	1
$1m–$10m	0	0	0	0	0	0	0
Total	100	100	100	100	100	100	100

(Fig. 3.5, Table 3.5). Though small, these businesses are definitely not start-ups, as over two-thirds have been in operation for three years or more (Fig. 3.6, Table 3.6). This is in keeping with common patterns globally where small business lending is restricted to only established firms that can show some operational track record.

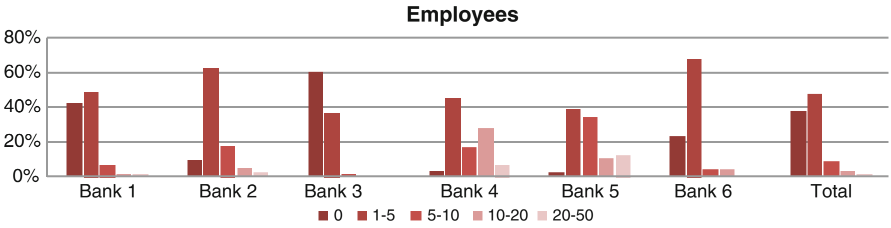

Fig. 3.5 Numbers of employees

Table 3.5 Numbers of employees

	Partner						
Employees	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
0	42	10	60	3	2	24	38
1–5	48	62	37	45	38	68	48
5–10	7	18	2	17	34	4	9
10–20	1	6	1	28	11	4	4
20–50	1	2	0	7	13	1	2
50–100	0	2	0	0	0	0	0
More than 100	0	0	0	0	2	0	0
Total	100	100	100	100	100	100	100

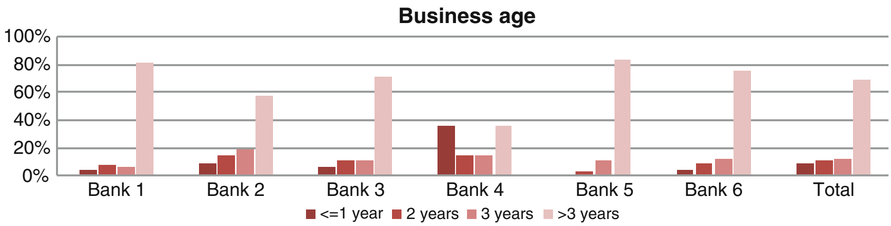

Fig. 3.6 Business age

Table 3.6 Business age

	Partner						
Business age	Bank 1 (%)	Bank 2 (%)	Bank 3 (%)	Bank 4 (%)	Bank 5 (%)	Bank 6 (%)	Total (%)
<=1 year	5	9	7	35	1	4	9
2 years	8	15	11	15	3	8	11
3 years	6	18	10	14	11	12	12
>3 years	81	58	71	35	84	76	69
Total	100	100	100	100	100	100	100

Outcome Measures

In evaluating the contribution of psychometric instruments to better identify high-potential entrepreneurs and direct finance to their ventures, there are two principal outcomes of interest: business performance (best represented with company profits) and loan repayment (i.e., did the person default).

Loan repayment is a particularly interesting outcome variable, because it is traditionally considered to be composed of two elements: ability to repay and willingness to repay.

Ability to repay will be driven by the ability of the entrepreneur. Though it is also influenced by the dynamics of the business, industry, and country in which the entrepreneur operates. Better entrepreneurs will presumably select better industries and will better adjust to and profit from changes to their environment.

Willingness to repay may be due to simple strategic calculations of the borrower (the costs of default are lower than the value of the capital retained) or driven by other individual level differences such as the level of commitment and honesty of the borrower.

Unfortunately it is usually not possible to know if an individual defaulter did not repay because of ability or willingness, but it is important to keep in mind that both factors may be contributing. And from the lender's perspective, it is not as important which of the two is the cause. What they care about is only if default can collectively be predicted and avoided with psychometric-enabled credit scoring.

Unlike default, which is independently and externally measured, business profits in this study are self-reported by the entrepreneurs completing the assessment. Therefore, the figures could be subject to misreporting. On the one hand, there is an incentive to understate profits, out of the worry that figures will be reported to the tax authorities and most small businesses underreport taxable profits. On the other hand, there could be an incentive to overstate profits, to appear more successful to the bank in case the business owner wanted to apply for another loan in the future. To minimize this risk, all entrepreneurs answered these and all other questions on the assessment on their own, outside of the view of bank officials. Moreover, they were told explicitly that their responses to financial questions would neither be shared with the financial institution nor to the government.

Business profits are self-reported and have been converted to monthly US dollar amounts. In terms of default, we adopt a definition of 30 days or more in arrears, that is, if the business owner missed a complete monthly payment cycle at any point in the past 6 months and therefore for some time owed the lender two or more payments. Because defaulters tend to make up a small percentage of total bank clients, we pursued stratified random sampling and over-sampled clients with repayment problems. This stratification was achieved with varying degrees of success, as can be seen in the summary statistics below, but resulted in an overall sample of 1,580 small business owners, just under 30 % of which had an arrears incident in recent history and were therefore labeled as "bads" to use the standard terminology of credit scoring (Tables 3.7 and 3.8).

Table 3.7 Sample size and composition by bank

Default rate at 30 days	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Total
Goods	240	175	371	155	64	105	1,110
Bads	173	167	68	11	23	28	470
Default rate (%)	41.9	48.8	15.5	6.6	26.4	21.1	29.7

Table 3.8 Average business profits by bank

	Partner	Mean
Business profits USD	Bank 1	1,267
	Bank 2	1,846
	Bank 3	830
	Bank 4	7,362
	Bank 5	3,606
	Bank 6	1,880

Appendix 2 features a table with summary statistics of the psychometric assessments detailed above: The Big Five, integrity, digit span, and Ravens Progressive Matrices scores. All variables have been standardized, other than digit span which is shown in number of digits, to facilitate comparisons of economic impact in the regression results.

Generally, we can see that the mean scores across the Big Five are within one standard deviation of the overall sample mean but with stronger differences between banks in the neuroticism, extroversion, and conscientiousness scales. The integrity and intelligence scales feature some differences, with banks 2, 4, and 5 clients scoring higher on both digit span and Ravens than the others. Interestingly, these are also the banks serving larger SMEs with higher levels of profits and numbers of employees (see Tables 3.5 and 3.8).

Procedure

The authors approached numerous financial institutions across Africa and Latin America to participate in this research project, eventually obtaining the participation of the six banks described above. Additional banks agreed to participate and launched testing but withdrew from the project after administering very few assessments.

For participating banks, the researchers first held a series of workshops with senior management and stakeholders explaining the goals of the testing and designed a rollout plan. While each plan varied slightly by institution, they all followed the same general setup.

First, loan officers were presented the project, to better understand their borrowers so that in the future, they could make lending decisions with more accurate and useful information about applicants. The loan officers were not mislead in any way about the nature of the testing and were instructed in detail as to the importance of engaged and active participation by their clients: The assessments had to be filled out in as "high stakes" a setting as possible, meaning the business owners were trying to "do well" on the assessment rather than completing it as a meaningless market survey. As explained below, this is important in order to simulate as closely as possible the incentives in place if this tool were implemented in practice.

Second, loan officers were trained on how to use the assessment platform. All the assessments were loaded onto a computer-based survey platform to ensure uniform implementation of interactive assessment components such as the digit span recall exercise. Officers were taught how to use the hardware, launch the assessment, and save the results upon completion.

Most importantly, loan officers were trained on how to present the assessment to clients. There was an introductory script provided to all participants, as well as an informed consent form that was signed (both available upon request). Officers were instructed to give clients any help requested with using the computer hardware (e.g., the mouse) and software (e.g., how to progress from one question to the next). In addition, they were instructed to provide any help requested by the applicant regarding vocabulary comprehension, but limited to the meaning of a word or phrase and not extending to suggested answers to questions. Officers were explicitly instructed to give no opinions on the question answers, no help on the questions with correct and incorrect answers such as the digit span and Ravens Progressive Matrices, and to ensure that clients did not use a pen and paper while taking the digit span test.

After training, loan officers tested samples of clients. In order to participate, a client had to have a loan product with the bank for at least 6 months and had to be both the legal counterpart for the loan and the owner/manager of the business. Cases where a business was co-managed by multiple owners or the loan was in the name of an owner not active in the daily management and strategic decision-making of the business were excluded from the sample. Researchers explained these characteristics to loan officers, who in some cases also received lists of testable clients from management. Loan officers were given monthly targets for numbers of clients tested, with separate targets for clients in good standing and clients in arrears. Researchers selected a small subset of tested clients from each of the four largest samples (banks 1 through 4) and directly contacted the clients to confirm that they did complete the assessment (to ensure officers weren't completing the tests themselves). Altogether, over 1,500 clients were tested across these six institutions, with response rates from 45 % to 80 % depending on the institution.

In order to give clients the incentive to actively participate, clients were informed prior to testing that if they participated, they would have the opportunity to win one of the netbook computers used for testing. Moreover, to simulate higher stakes, applicants were informed that their chances of winning would increase if they did "better" on the assessment. The assessment questions with correct/incorrect answers were graded and each participant had their name added to the draw one extra time for each correct answer. Though some clients requested feedback on their assessment scores, they were told from the outset that this would not be possible, as the measurement and interpretation of personality constructs is a specialized function of psychologists.

Clients were informed that their answers would be confidential, particularly for financial questions where this was repeated in the text of each question. The answers would not be shared neither with the bank (to avoid over-reporting to seem like "better" clients for future loans) nor the tax authority (to avoid underreporting to avoid taxes). The financial question about profit levels was not asked in the first wave of assessments and only subsequently added, reducing the number of observations against that outcome variable as compared to default behavior.

Chapter 4
Results and Discussion

Abstract This chapter examines the relationships between psychometric assessments and the entrepreneur's business performance (profits) and credit risk (default). Regarding the Big Five personality traits, extroversion is found to be strongly related to higher profit levels, with weaker relationships for agreeableness (positive) and conscientiousness (negative). Interestingly, integrity is found to have a weak negative relationship with profits: the most honest entrepreneurs aren't the most honest. Conversely, when considering default risk, the lowest-risk entrepreneurs also tend to score higher on the integrity assessment, as well as register higher levels of conscientiousness. Digit span (fluid intelligence), controlling for level of education, is negatively related to profit levels, but is not related to default risk. When combined, these relationships with conscientiousness, honesty, and level of education have an AUC (a common metric of credit score predictive power) of 0.57–0.66, which is not extraordinarily strong when compared to credit scoring models in high-information countries and market segments, but it is sufficient to add significant value to the risk analysis task facing banks lending to SMEs in emerging markets. We show that for one of the sample banks, risk of default for low-scoring clients is 50 % higher than it is for high-scoring clients. Furthermore, we show that these results can be improved by customizing models to each country and financial institution, which isn't surprising given the cultural differences between Peru, Colombia, Kenya and South Africa. While traditional methods of model building suffer challenges of doing this customization without large amounts of data, new methodologies such as Bayesian methods are shown to offer promise to improve results even further, making customization without over-fitting possible and further strengthening the case for using psychometric tools for credit risk analysis.

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Table 4.1 Correlation matrix

	Default	Profits	Revenues	Employees	Nueroticism (-)	Extraversion	Openness	Agreeableness	Conscientiousness	Integrity	Digit span	Ravens	Age (in cohorts)	Education	Male
Default	1														
Profits	0.02	1													
Revenues	0.01	0.56	1												
Employees	0.01	0.49	0.56	1											
Nueroticism (-)	-0.14	0.11	0.18	0.17	1										
Extraversion	-0.04	0.23	0.29	0.27	0.50	1									
Openness	0.04	0.09	0.06	0.08	0.04	0.31	1								
Agreeableness	-0.04	0.05	-0.05	-0.08	0.20	0.28	0.16	1							
Conscientiousness	-0.08	0.01	0.00	-0.04	0.26	0.31	0.06	0.35	1						
Integrity	-0.18	-0.04	0.01	-0.02	0.26	0.24	-0.02	0.19	0.37	1					
Digit span	-0.01	0.04	0.17	0.12	0.16	0.30	0.10	0.05	0.06	0.04	1				
Ravens	0.08	0.20	0.36	0.25	0.15	0.30	0.12	-0.02	0.05	-0.04	0.32	1			
Age (in cohorts)	-0.06	0.00	-0.03	-0.03	-0.01	-0.08	-0.13	0.01	0.07	0.14	-0.16	-0.16	1		
Education	0.07	0.26	0.29	0.30	0.21	0.35	0.19	0.01	0.06	0.00	0.27	0.34	-0.17	1	
Male	0.00	0.23	0.23	0.22	0.02	0.12	0.15	0.00	0.02	-0.08	0.11	0.17	0.02	0.05	1

In order to evaluate the potential contribution of psychometrics to resolving the constraints to finance facing small businesses in emerging markets, we will investigate two questions. First, what is the relationship between the measured variables and business success (i.e., profits)? Second, what is the relationship between the measured variables and credit risk (i.e., the probability of default)?

Though clearly related, these are potentially different questions. Entrepreneurs that are more successful entrepreneurs with higher profits would likely have a greater ability to repay, but not necessarily the willingness to repay. So in one sense, we could consider the results on business profits as reflecting ability to repay and the results on default the combination of ability and willingness to repay.

The psychometric dimensions under consideration may relate differently to the two outcomes. As mentioned earlier, higher integrity may be related to lower credit risk through a lower willingness to walk away from contracts and default. But on the other hand, it may have a different relationship with profitability: The most honest entrepreneurs may not be the most successful. So comparing the relationships across these two outcomes is revealing.

First, we show the pairwise correlations above (Table 4.1). Entrepreneurial performance has the highest correlations with extraversion, fluid intelligence (Ravens Progressive Matrices), and level of education. The overall strength of the correlations of these psychometric variables is lower with default than it is with profitability. This is unsurprising, both because default is a binary variable with inherently restricted range (more appropriately tested using logit regression, for example), whereas profits are a continuous variable with greater variance, and second because default is an outcome that could very well be more difficult to predict because it may mix together highly differing types of entrepreneurs such as the dishonest and successful (has business profits to repay but can get away with default), the honest and unsuccessful (business in decline), and simply the unlucky (a sick relative or market shock put them a few months behind in their loan payments).

The largest correlations with default are different from self-reported firm profits: Lower neuroticism and higher integrity most strongly relating to lower default levels (Table 4.1). Conscientiousness is also negatively related to default risk, but fluid intelligence (measured by the Ravens Progressive Matrices) is actually positively related to risk of default, as is level of education, which is somewhat counterintuitive if one would think of intelligent entrepreneurs as more able to grow their businesses and avoid default. However, this could be either because fluid intelligence isn't as important for business success (e.g., its better if an entrepreneur is single-mindedly focused on running their business rather than being intellectually curious) or because many intelligent entrepreneurs know they can either get away with default or use temporary default as a way to manage their cash more effectively.

These rather crude pairwise relationships suggest that default may be a harder outcome to predict with these psychometric variables than firm profitability and that the individual drivers of each may also differ substantially. Moreover, there is a large degree of intercorrelations among the psychometric variables, particularly among the Big Five and integrity measures, but also among our two measures of intelligence and between intelligence and some of the Big Five (particularly extraversion). Only using a multivariate regression can we observe the contribution of each dimension—conditional on the other dimensions being statistically controlled.

Moreover, the motivating question of this research is if these assessments help unlock access to credit, so our interest is the overall combined contribution of these psychometric assessments to the prediction of business potential and default, rather than their pairwise correlations. If one were to perform credit scoring, but instead of using borrowing history and other financial data which firms cannot provide, you were to use these psychometric assessments, would you be able to predict risk of default in a meaningful way?

A way to answer this question is to combine the assessments into a predictive multivariate model.

Identifying the Best Entrepreneurs: Regression Analysis

Table 4.2 shows the multivariate regression results to examine which psychometric characteristics are associated with a higher profitability entrepreneurs and higher frequency of default. We perform a linear ordinary least squares regression on the natural log of profits, as well as logit regressions separating the sample into "high-" and "low-"profit entrepreneurs at each of the 10th, 50th, and 90th percentiles. This is to allow for different relationships at different profitability levels, as one particular dimension may differentiate the very worst entrepreneurs from the rest but not the very best entrepreneurs from the rest, or vice versa.

There are a number of interesting results in Table 4.2.

Table 4.2 Multivariate results without bank fixed effects

Model	OLS				
Partner dummies	Not included	Logit			
Dependent var	LN Business profits in US dollars	(Client has profits in the top 90 % across partners = 1)	(Client has profits in the top 50 % across partners = 1)	(Client has profits in the top 10 % across partners = 1)	Default
Nueroticism (−)	0.02	0.17	0.06	−0.1	−0.28***
	(0.540)	(1.090)	(0.700)	(0.670)	(3.660)
Extroversion	0.21***	0.43***	0.35***	0.62***	−0.08
	(4.770)	(2.600)	(3.440)	(3.410)	(0.950)
Openness	−0.05	−0.16	−0.08	−0.31**	0.1
	(1.320)	(1.150)	(0.960)	(2.320)	(1.440)
Agreeableness	0.03	0.36**	0.09	−0.02	0.08
	(0.850)	(2.270)	(0.990)	(0.110)	(0.940)
Conscientiousness	−0.04	−0.16	−0.06	−0.2	−0.07
	(1.140)	(1.110)	(0.680)	(1.520)	(1.000)
Integrity	−0.09***	−0.37***	−0.19**	−0.01	−0.37***
	(2.590)	(2.650)	(2.440)	(0.050)	(5.100)
Digit span	−0.11***	−0.29**	−0.12	−0.21*	−0.1
	(3.310)	(2.310)	(1.630)	(1.680)	(1.470)
Ravens	0.10***	0.12	0.11	0.32***	0.23***
	(3.010)	(0.840)	(1.330)	(2.650)	(3.360)
Age (cohorts)	0.02	0.1	0.09	−0.05	−0.03
	(0.700)	(0.860)	(1.290)	(0.480)	(0.540)
Education	0.19***	0.25	0.44***	0.35***	0.23***
	(5.270)	(1.610)	(5.170)	(2.630)	(3.220)
Male	0.36***	1.07***	0.74***	0.74***	−0.08
	(5.710)	(3.800)	(5.140)	(3.040)	(0.640)
Profits					
Constant	−0.69***	1.33**	−1.60***	−3.44***	−1.36***
	(4.890)	(2.340)	(4.830)	(6.440)	(4.810)
Observations	963	963	963	963	1,434
# of ones		869	465	97	428
R-squared	0.16				
Pseudo R-squared Adj		0.06	0.07	0.06	0.05
AUROC_All		0.63	0.61	0.62	0.67
AUROC Bank 1		0.71	0.66	0.59	0.61
AUROC Bank 2		0.67	0.6	0.71	0.64
AUROC Bank 3		0.64	0.66	0.62	0.63
AUROC Bank 4		0.41	0.35	0.69	0.54
AUROC Bank 5		0.73	0.61	0.68	0.67
AUROC Bank 6		0.71	0.53	0.55	0.71

Absolute value of t statistics in parentheses

In = natural logarithm, *AUROC* = Area under the receiver operating characteristic curve (see below)

*significant at 10 %;** significant at 5 %;*** significant at 1 %

First, looking at the contribution of the Big Five, we see that extroversion is strongly positively related to higher levels of profitability, at all levels. However, it has no strong relationship to default. Neuroticism, however, has the opposite characteristic: It is not related to business profitability but is strongly related to default (lower neuroticism going with a lower risk of default). Interestingly, though conscientiousness is a common predictor of success in various employment settings, in this case it is not strongly related to either business performance or default risk, once the other dimensions are controlled for. There is a positive relationship between agreeableness and business performance at the lower levels, meaning higher agreeableness is observed in the majority of decently performing entrepreneurs as compared to the least profitable. And finally there is a negative relationship between openness and profitability at the other end of the spectrum, meaning that the highest-profit entrepreneurs tend to be characterized by lower openness to experience than the rest.

The results on integrity are quite interesting. They are strongly negatively related to profitability, particularly at the lower-profit levels of the sample. So the lowest-profit entrepreneurs feature a statistically significantly higher level of integrity than the rest, or in a nutshell, the worst entrepreneurs tend to score higher on integrity assessments. On the other hand, integrity is also strongly negatively related to default: Less honest entrepreneurs default more often. So if you are lending money, you want to lend it to more honest entrepreneurs, but if you want to predict who will be more profitable, you would probably steer clear of the most honest entrepreneurs.

Digit span recall is negatively related to business profits, though not default. However, it is important to note that this is controlling for fluid intelligence as measured by the Ravens Progressive Matrices, so it is possible that the positive relationship between intelligence and business performance is being captured by the matrices and the orthogonal component of digit span has an alternative interpretation. The score on Ravens Progressive Matrices is positively related to company profits, but only for the highest-profit firms in the sample. Interestingly, the relationship between default and fluid intelligence (as measured by the Ravens matrices) is also positive, meaning that better-scoring entrepreneurs default more often. The exact same pattern holds with the level of education: positively related to profitability but also default risk.

One important feature of these results is that they do not include bank fixed effects, meaning there are relationships both within and across the banks included in the sample. Looking across financial institutions maximizes the amount of variance we have in the sample and allows for the investigation of the broader patterns between lenders and countries. However, all of these financial institutions operate within a single country and are interested in the predictive power of the tool within their own context rather than across their international peers. Moreover, looking across institutions allows for cross-country and cross-institution factors to confound the relationships. For example, banks 5 and 6 serve larger more successful entrepreneurs than banks 1 and 3, but they are also in different countries. It is possible therefore that the regressions above are ascribing differences in psychometric scores due to cross-country differences to differences in profit levels.

We can adjust for this possibility by including bank fixed effects in the regression and examine the relationships with profitability and default exclusively within each institution, rather than across the institutions. The following table shows the results controlling for fixed effects with dummy variables for five of the six banks (resulting coefficient estimates are excluded for brevity).

This is a stricter test of relationships because it reduces the variance in the outcome variables. Instead of using the wide differences in psychometric outcomes found across all of these financial institutions, these regressions only measure the within-bank relationships. Each of these banks limits their lending to particular segments of the market, for example, offering only microloans to micro-enterprises or offering only medium-sized loans to firms with larger revenues. By including partner fixed effects, we are no longer considering these wider differences and instead measuring the differences in psychometric variables among entrepreneurs within those limited segments of the market served by the bank. In other words, we are no longer comparing microcredit clients to small business clients and instead considering only differences among clients served by the same bank. This is a more difficult test statistically because there is much less variation in the explanatory variables; the results are likely to be much clearer of external confounds like country cultural characteristics.

Looking only at the factors distinguishing profitability and credit risk within financial institutions, we do see some differences compared to the results without bank fixed effects. In the Big Five, the links with extroversion and agreeableness remain the same as those between banks in Table 4.2. However, neuroticism's relationship with default is now statistically insignificant, and conscientiousness now becomes strongly related to default: Lower conscientiousness entrepreneurs have a higher default risk. The results on integrity and digit span remain, but the Ravens matrices no longer strongly distinguish profitability even at the highest percentiles (within banks).

How does this relate to the previous literature? As noted, past studies on entrepreneurial outcomes typically look at venture formation and success, but not default risk. Focusing on the relationships with firm profitability, we see that the Holland (1985) hypothesized "E-type" of personality (comprised of high conscientiousness and extraversion, lower agreeableness and neuroticism, and neutral optimism) is partially supported by these results. Table 4.3 shows strong positive relationships with extraversion and weaker negative relationships with neuroticism. Unlike the hypothesized E-type, however, we do not see a positive relationship with conscientiousness nor do we see a negative relationship with agreeableness. In fact, we see a weak relationship in the opposite direction. And across banks we do find that the highest profitable entrepreneurs are distinguished by a weakly lower level of openness.

The fact that our results show the strongest differences on extraversion is somewhat surprising as this is the one dimension of the Big Five on which Zhao and Seibert (2006) found no differences between entrepreneurs and non-entrepreneurs. At the same time, they found the strongest relationship between entrepreneurial status and conscientiousness, which in our data does not differ in a statistically

Table 4.3 Multivariate results with bank fixed effects

Model	OLS				
Partner dummies	Included	Logit			
Dependent var	LN Business profits in US dollars	(Client has profits in the top 90 % within partner = 1)	(Client has profits in the top 50 % within partner = 1)	(Client has profits in the top 10 % within partner = 1)	Default
Nueroticism (−)	0.01	0.24	−0.02	−0.30**	−0.1
	(0.270)	(1.400)	(0.180)	(2.050)	(1.110)
Extroversion	0.15***	0.32*	0.26***	0.47***	−0.1
	(3.530)	(1.820)	(2.630)	(2.730)	(1.040)
Openness	−0.03	−0.06	−0.12	−0.02	0.06
	(0.750)	(0.410)	(1.520)	(0.170)	(0.740)
Agreeableness	0.05	0.29*	0.01	0.17	0.03
	(1.390)	(1.740)	(0.100)	(1.120)	(0.310)
Conscientiousness	−0.05	−0.28*	0.03	−0.09	−0.29***
	(1.320)	(1.750)	(0.340)	(0.670)	(3.540)
Integrity	−0.07**	−0.25*	−0.1	−0.11	−0.30***
	(1.980)	(1.700)	(1.300)	(0.850)	(3.880)
Digit span	−0.11***	−0.36***	−0.16**	−0.30**	−0.01
	(3.690)	(2.830)	(2.120)	(2.420)	(0.140)
Ravens	−0.02	−0.2	−0.11	0.09	0.08
	(0.510)	(1.270)	(1.220)	(0.610)	(0.940)
Age (cohorts)	0.03	0.21*	0.06	−0.02	0.03
	(0.990)	(1.700)	(0.940)	(0.220)	(0.430)
Education	0.16***	0.22	0.41***	0.29**	0.19**
	(4.580)	(1.380)	(4.750)	(2.200)	(2.460)
Male	0.30***	0.50*	0.62***	0.66***	−0.1
	(4.870)	(1.870)	(4.260)	(2.820)	(0.740)
Profits					
Constant	0.01	1.45**	−1.30***	−91***	−2.17***
	(0.030)	(2.360)	(3.820)	(5.440)	(6.670)
Observations	963	945	933	951	1,434
# of ones		869	465	97	428
R-squared	0.23				
Pseudo R-squared Adj		0.01	0.02	0	0.12
AUROC_AII		0.71	0.64	0.66	0.75
AUROC Bank 1		0.75	0.65	0.63	0.63
AUROC Bank 2		0.77	0.65	0.69	0.66
AUROC Bank 3		0.63	0.67	0.68	0.65
AUROC Bank 4		0.57	0.33	0.65	0.56
AUROC Bank 5		0.65	0.6	0.72	0.65
AUROC Bank 6		0.67	0.53	0.63	0.67

Absolute value of t statistics in parentheses

Note: Estimates include fixed effects by bank, estimated coefficients omitted for brevity

* significant at 10 %;** significant at 5 %;*** significant at 1 %

significant way between low- and high-profit entrepreneurs. This may be due to the difference discussed above, between entrepreneurial status (i.e., entrepreneur or manager) and entrepreneurial *performance* (high-profit or low-profit entrepreneur). In addition, most of the studies included in their meta-analysis are with highly educated managers and entrepreneurs in "developed" countries, rather than the small business samples in "emerging" markets that appear in our study.

Recall Ciavarella et al. (2004) had one differing prediction from these other studies that agreeableness would actually be positively related to entrepreneurial outcomes. They also had one opposite empirical finding that openness is negatively related to entrepreneurial outcomes. Both of those are weakly supported in our results, with lower openness distinguishing the highest-profit entrepreneurs from the rest when excluding bank fixed effects (i.e., between banks—Table 4.2) and higher agreeableness distinguishing the majority of entrepreneurs from the lowest-profit earners among them, both within and across banks. The finding on openness in particular supports their hypothesis that conditional on deciding to become an entrepreneur, which could be positively related to openness, that trait then becomes a liability when relating to success. Ciavarella et al. (2004), however, did not find relationships between extraversion and venture survival, while in our data extraversion is strongly related to business profitability in all specifications.

Both Tables 4.2 and 4.3 show a positive relationship between educational attainment and entrepreneurial success as measured by profit levels, which is consistent with De Mel et al. (2008) finding of a positive link between education and returns to capital. However, the opposite is found relating to default risk, both within and across banks: Higher education is associated with higher rates of default. This again illustrates how different definitions of the entrepreneurial outcome of "interest" can have strong effects on success. One hypothesis mentioned above was that educational attainment was an imperfect proxy for intelligence that included noise due to differential access by socioeconomic status. Yet, the positive relationship between education and both profits and default remains even when controlling for fluid intelligence measured by the Ravens Progressive Matrices and digit span recall.

Given the evidence relating digit span positively to selection into entrepreneurship (Djankov et al. 2005, 2007) and success at entrepreneurship (De Mel et al. 2008), our finding of a strong and consistently negative relationship between digit span and self-reported profits is surprising. However, this is controlling for the score on the Ravens Progressive Matrices, which are also a test of intelligence. The simple pairwise correlation between digit span and profitability is positive rather than negative, but it is very small. Ravens Progressive Matrices, considered by some to be the best of all nonverbal intelligence tests, have not been investigated in studies of entrepreneurs to our knowledge, and the findings here are mixed with a positive relationship between intelligence and profits looking across all countries and banks, but not within them. This could potentially be due to a weak statistical relationship, which is insufficient to emerge from within-country analysis, or also could be because scores on the Ravens matrices are correlated with other important cross-country determinants of firm profitability, such as macroeconomic stability or productive business ecosystems.

In terms of policy implications of these results, it would be tempting to read the tables above and conclude that countries could create more high-profit entrepreneurs by promoting higher levels of education and extraversion (as well as limited honesty and digit span recall). This would be extremely misguided, however, because as detailed in the outset, these results indicate nothing regarding the direction of causality, so it does not necessarily hold that increasing any of these dimensions (if that were possible). But in terms of enabling greater finance for small business owners, the results are more informative. They suggest that psychometric tools could potentially help, if they have sufficient overall predictive power, to enable increased lending and entrepreneurial growth in emerging markets.

Overall Predictive Power

What is the overall predictive power of these variables?

In terms of predicting which entrepreneurs are likely to be high or low profit, we can examine the relative probabilities at different scores on the various psychometric assessments. For example, in the 90th percentile of extraversion and education level but the 10th percentile of integrity and digit span has, on average, profits that are *five times higher* than an individual at the opposite side of both spectrums, according to these results.

In terms of predicting default risk, we, like the banks, want to know how well a credit score based off the model presented above would perform for lenders seeking to take advantage of the significant demand for entrepreneurial finance while controlling risk. There are a common set of metrics used to assess credit scores. It is important to remember that any credit score does not give a decision to accept or reject an applicant—it is a continuous relative measure of risk, and lenders can make an accept/reject decision based on any score cutoff. Metrics to assess the predictive power of credit scores therefore evaluate the score's ability to sort applicants by their credit risk. If a score is closely related to default, then those with a low score should be much more likely to default than those with a high score. Credit scores with little value for directing lending do not separate the high-risk from low-risk applicants as well, and both are evenly distributed across the score's spectrum.

This ability of a model to sort applicants based on their level of default risk is typically illustrated by a receiver operating characteristic curve, or ROC curve. This curve plots on the x-axis the percentage of "goods" (non-defaulters) below any particular score level, while the y-axis shows the percentage of "bads" (defaulters) below that score. Any credit score represents a curve on this graph, with each point on the curve showing the impact of a potential cutoff score (Fig. 4.1).

A perfectly predictive credit model would assign the lowest score to all the defaulting clients, and therefore, in this graph if you started rejecting applicants with the lowest score, you would only reject defaulters, meaning a move up of the y-axis while the x-axis remains at 0 %. And only after raising the rejection score cutoff to the point that all 100 % of the bads were rejected (the top-left corner of the

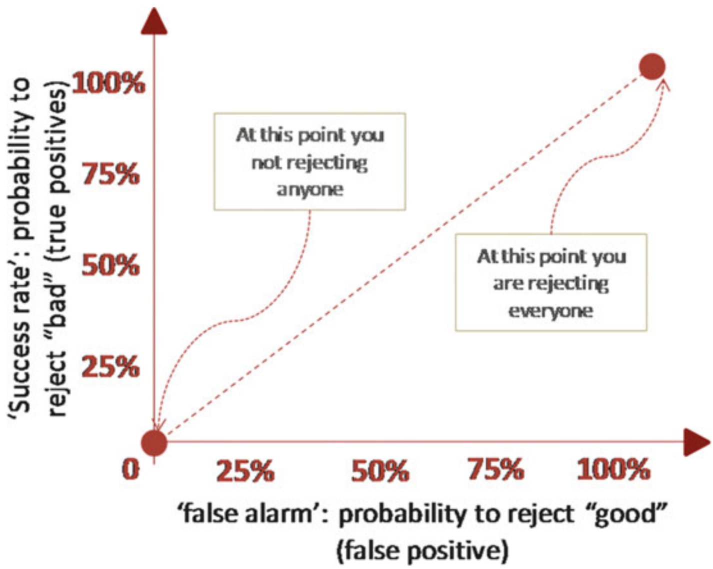

Fig. 4.1 Building an ROC curve

graph) would raising the rejection score cutoff start rejecting the goods, moving from the top-left corner horizontally along the y-axis until it reaches the maximum score and all applicants would be rejected (top-right). So the ROC curve for a perfectly predictive credit score would appear as the top-left side of a square Fig. 4.2.

Conversely, the ROC curve for a credit score containing no predictive power would not distinguish bads from goods at any level of the score—it is the equivalent of flipping a coin. This means goods and bads would be evenly distributed across all scores. So in Fig. 4.3, beginning from the lowest score and increasing the rejection score cutoff would lead to a rejection of both goods and bads in equal proportion. In other words, the ROC curve would be a straight diagonal line.

As can be seen between these two extremes, a better credit-scoring model will be more like Fig. 4.2 than 4.3, bowed up and to the left, placing a greater proportion of bads at lower scores and a greater proportion of goods at higher scores.

To summarize this performance, the credit-scoring industry typically summarizes a model's power using the area under the ROC curve or AUROC. The perfectly predictive model above has an AUROC of 1, while the useless model has an AUROC of 0.5. Hence the higher an AUROC, the better the model.

The AUROC for the psychometric-based score is shown at the bottom of Table 4.3 above and is illustrated on a bank by bank in Fig. 4.4 below.

Focusing on the more relevant model built using bank dummies, we see the AUROC ranging from a low of 0.57 in bank #4 to 0.67 in bank #6, and an overall average of 0.64. There are no hard-and-fast benchmarks for levels of AUROC that are sufficient for credit scoring, as it greatly depends on the business context. Moreover, AUROC is only a summary metric of overall sorting power of a model, and strictly speaking cannot be directly compared across samples as it is dependent

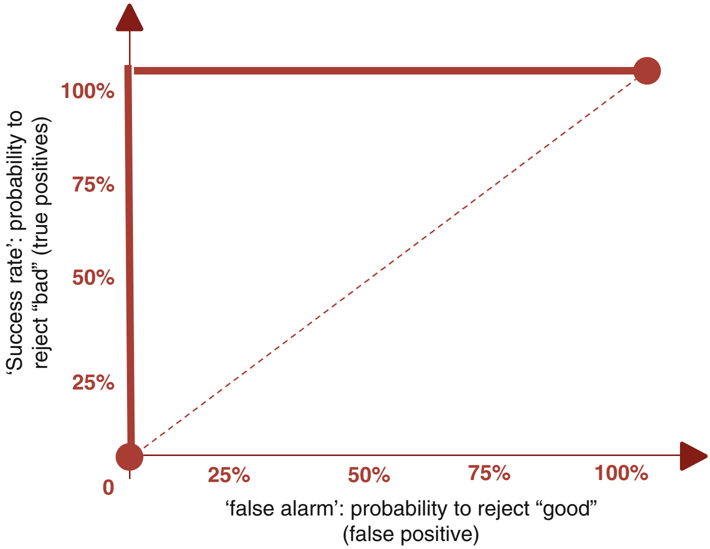

Fig. 4.2 ROC curve for a perfect credit-scoring model

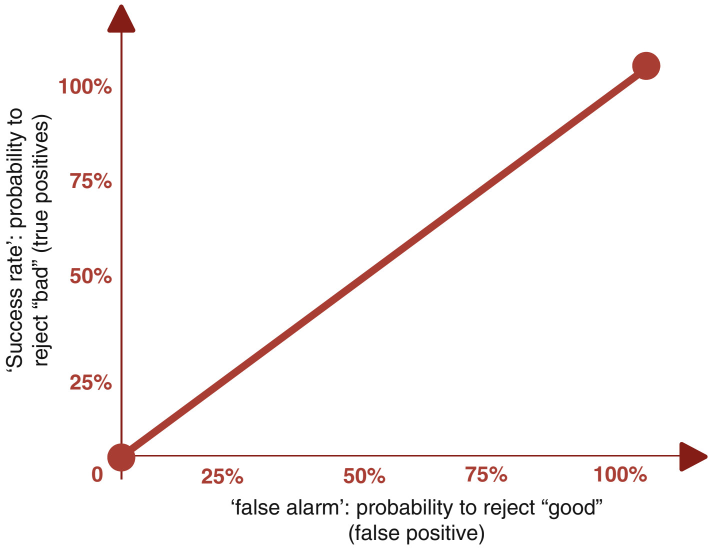

Fig. 4.3 ROC curve for a useless credit-scoring model

on the overall bad rate. But it is the most common metric used in industry, and as a rough rule of thumb among some commercial banks in emerging markets, scores with an AUROC of 0.6 or greater provide some valuable information for application scoring in information-scarce environments, with AUROCs of 0.7 or greater typical from scorecards in more information-rich environments.

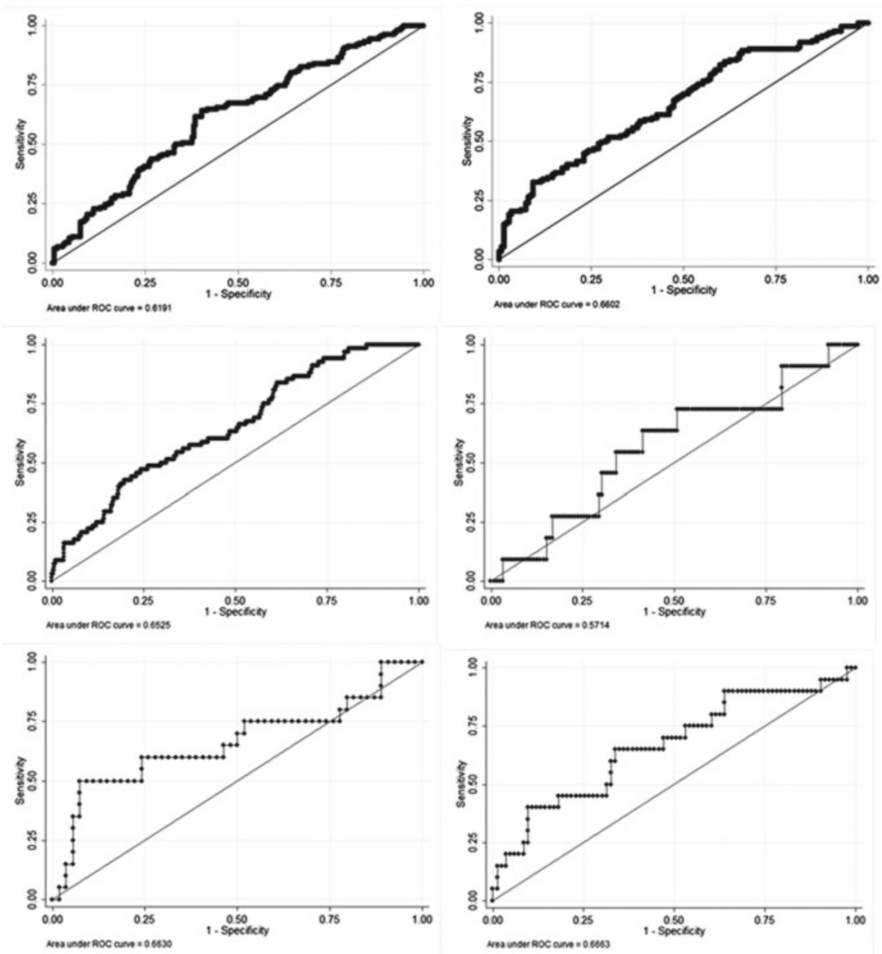

Fig. 4.4 ROC curves for banks 1–6

An overall score, primarily driven by evaluations of conscientiousness, integrity, and level of education and their relationships that are then averaged across all six banks and four countries and cultures, achieves the 0.6 benchmark in all of the different organizations (banks) but one. This moderate predictive power suggests that these global psychometric relationships may not be sufficient in all contexts, but they do show the promise to contribute to lending decision-making, particularly in information-scarce contexts. And small- and medium-enterprise finance in emerging markets is difficult precisely because it is such an information-scarce environment: The fact that this score can be generated without depending on nonexistent financial data and borrowing history makes it all the more important.

To illustrate the impact that such a model could have if implemented for credit decision-making, let us take bank #6 as an example, with an AUROC of 0.67. In our sample of bank #6's clients, 49 % of them had experienced at least one late repayment of their loans in the prior six months. But by setting a cutoff at the 50th score percentile, this late repayment rate is 60 % for those below and 40 % for those above. In other words, having a low score compared to a high score increases the risk of default by 50 % (from 4/10 to 6/10). Banks could use this information to give those lower-scoring applicants additional risk evaluation or increased security requirements. Or the bank could use the score to pre-screen out those lowest scoring 10 % who have a 76 % arrears rate, so that the efforts of their loan officers can be better focused on the lower-risk population. Another potential use is to fast track the applications of the top-scoring 5 % who only had an 18 % arrears rate (remember, that is 18 % having a case of one 30 days or more arrears instance in their loan, not the default rate which is much lower).

All of these examples illustrate using the score by itself, but one of the most common uses would be to combine the score into a larger risk model that incorporates other factors, like demographic data, historical data, and behavioral data (when available), to create a more full and complete risk profile of the applicant, which would greatly facilitate increased lending to the SME segment. In an information-scarce setting, a tool that can signal a 50 % increase in default risk is a useful signal and can identify a profitable subset of an overall population that is too risky to lend to and otherwise indistinguishable. This would be a very valuable outcome both for the entrepreneurs that could now gain access to credit as well as to the banks who could lend to them.

Country-Level Comparison

In the analysis above, we examined the drivers of entrepreneurial performance and credit risk across countries and also within countries using country fixed effects. However, these fixed effects regressions were still pooled, with the results averaging across all countries in the sample. In other words, we are building the models based on the average relationships that hold across all banks, countries, and cultures in the sample, averaging out country particularities. The resulting predictive power of such a "global" psychometric-based model of default or entrepreneurial performance shows consistent predictive power across all countries in the sample, despite including countries as different as Colombia, Peru, South Africa, and Kenya.

There is an argument for some universal drivers of entrepreneurial performance that would consistently hold across countries. Though economies and cultures vary across countries, many of the tasks that an entrepreneur must perform are similar, such as raising capital, overcoming barriers, organizing production, and sales. Moreover, many entrepreneurs work successfully and seamlessly across countries. In addition, those who must evaluate entrepreneurial potential like Venture Capital and Angel investors also work across countries and cultures. And this is not limited to developed countries, as shown by investment companies like Acumen Fund and Aureos Capital, which combine local knowledge with international investment professionals who evaluate entrepreneurs across many culturally diverse emerging markets.

Cross-country evaluations of psychometric instruments like the Big Five and others have mixed results. In general, it is considered difficult to directly compare different cultures on dimensions such as the Big Five, because "any observed differences may exist not only because of a real cultural disparity on some personality trait but also because of inappropriate translations, biased sampling, or the non-identical response styles of people from different cultures" (Schmitt et al. 2007). It is therefore difficult to establish if, and to what degree, personality traits may tend to differ across countries.

But as noted above, what is important for the ability to use similar psychometric tools in credit scoring across multiple countries is not that such traits tend to be the same level or even have the equivalent meaning, prevalence, relevance, or factor structure across countries. What *is* needed is relatively consistent relationships between such assessments and entrepreneurial performance or default behavior across multiple countries. This is what is shown above to hold, at least to some degree. For instance, though extraversion has been found to be the dimension of the Big Five that varies most systematically across countries (Schmitt et al. 2007), our sample of results shows that even within countries it continues to hold a large degree of predictive power for firm profits.

Yet, it is reasonable to expect that given cross-country heterogeneity in our sample, while some traits associated with entrepreneurial success might hold across countries, others may differ by economy, culture, and other country characteristics such as political system and market conditions. Predictive models used to more efficiently direct resources to entrepreneurs based on psychometric instruments would in that case improve with country customization. And as pointed out in Caliendo and Kritikos (2012), an important unanswered question is do the same personality characteristics play the same role in both high-income and low-income countries?

We can address this question within our data. While limited to Africa and Latin America, data spanning countries as different as Kenya, South Africa, Peru, and Colombia are telling as to the stability of these drivers and the potential for a "global" versus a "nationalized" psychometric scorecard to identify high-performing and low-risk entrepreneurs.

Below we show country-level regressions on both profits and default. Only banks 1, 2, and 3 have samples of a sufficiently large size to be able to perform regressions and robustly test their predictive power out-of-sample (more details below).

Relating to business performance, we see that the two banks in Latin America (1 and 3) both feature the strong relationship between extraversion and business profitability, whereas agreeableness has a stronger positive relationship with profitability in bank 2, which is located in Africa. The counterintuitive relationship between digit span and profits, that is, that higher digit span is associated with lower levels of profitability controlling for the positive relationship between education and profits, is shown to be a feature of banks 2 and 3, though not in bank 1, and it is in conjunction with a strong positive relationship between profitability and education level in those two banks.

In terms of predicting default, these results show a lower degree of difference between countries and financial institutions, with conscientiousness and integrity holding nearly the same relationship across all three institutions (though different degrees

Table 4.4 Bank-customized models

	Bank 1		Bank 2		Bank 3	
Model	OLS	Logit	OLS	Logit	OLS	Logit
Dependent var	LN Business profits inUS dollars	Default	LN Business Profits inUS dollars	Default	LN Business Profits in US dollars	Default
Neuroticism (–)	–0.09	0.06	0.09	–0.04	0.02	–0.23
	(0.900)	(0.390)	(1.090)	(0.190)	(0.340)	(1.210)
Extroversion	0.23**	–0.1	0.03	–0.16	0.18***	–0.25
	(2.000)	(0.590)	(0.370)	(0.840)	(2.940)	(1.300)
Openness	–0.04	0.42***	–0.09	0.03	–0.02	–0.14
	(0.390)	(3.110)	(1.120)	(0.180)	(0.340)	(0.960)
Agreeableness	–0.03	–0.01	0.17**	0.01	0.06	0.22
	(0.310)	(0.060)	(2.230)	(0.060)	(1.030)	(1.210)
Conscientiousness	0.06	–0.39**	–0.09	–0.2	–0.03	–0.38**
	(0.610)	(2.420)	(1.250)	(1.340)	(0.660)	(2.260)
Integrity	–0.04	–0.28	–0.06	–0.27**	–0.11**	–0.29*
	(0.320)	(1.590)	(1.070)	(2.150)	(2.170)	(1.730)
Digit span	–0.01	0.18	–0.09*	–0.04	–0.11**	–0.06
	(0.050)	(1.190)	(1.760)	(0.320)	(2.360)	(0.420)
Ravens	0.03	0.05	–0.05	0.1	–0.05	–0.47
	(0.330)	(0.370)	(0.690)	(0.660)	(0.660)	(1.320)
Age (cohorts)	–0.06	–0.14	0.31***	0.36**	–0.03	0.06
	(0.930)	(1.310)	(4.590)	(2.350)	(0.700)	(0.520)
Education	0.07	–0.03	0.29***	0.59***	0.15***	0.40**
	(0.760)	(0.260)	(3.770)	(3.450)	(2.800)	(2.260)
Male	0.41***	0.22	0.11	–0.25	0.42***	0.05
	(2.810)	(0.990)	(0.920)	(0.950)	(4.490)	(0.150)
Constant	–0.24	0.13	−1.55***	–2.53***	–0.75***	–3.53***
	(0.680)	(0.250)	(5.320)	(3.750)	(3.500)	(4.720)
Observation	159	388	213	299	413	433
# of ones		162		147		68
R-squared	0.13		0.21		0.12	
Pseudo R-squared Adj		0.02		0.04		0.01
AUROC		0.67		0.71		0.68

Absolute value of t statistics in parentheses

*significant at 10 %;**significant at 5 %;***significant at 1 %

of statistical significance due to sample size). Most importantly, these two dimensions have a more consistent relationship with the probability of default than do the demographic variables that currently form the basis of many application scorecards, namely, gender, age, and level of education. This greater consistency in turn suggests that such psychometric indicators might actually be more reliable predictors of default than demographic proxies, even across countries, which is an interesting finding considering the fact that the majority of application scorecards for new-to-bank loan applicants rely heavily on demographic information from historical applications.

In terms of overall predictive power, we see from Table 4.4 that these customized models feature higher AUROCs than when applying a global model. This higher

Table 4.5 Bank-customized models with 20 % hold-out sample

	Bank 1	Bank 2	Bank 3
Model	Logit	Logit	Logit
Dependent var	Default	Default	Default
Neuroticism (–)	0.05	–0.05	–0.2
	(0.300)	(0.230)	(0.970)
Extroversion	–0.08	–0.1	–0.28
	(0.440)	(0.440)	(1.340)
Openness	0.51***	0.05	–0.19
	(3.250)	(0.250)	(1.150)
Agreeableness	–0.07	–0.13	0.33
	(0.400)	(0.660)	(1.610)
Conscientiousness	–0.34*	–0.07	–0.54***
	(1.870)	(0.430)	(2.670)
Integrity	–0.36*	–0.32**	–0.07
	(1.840)	(2.200)	(0.400)
Digit span	0.26	–0.01	–0.21
	(1.470)	(0.070)	(1.140)
Ravens	0.03	0.11	–0.36
	(0.180)	(0.670)	(1.010)
Age (cohorts)	–0.11	0.48***	0.02
	(0.940)	(2.770)	(0.150)
Education	0	0.60***	0.37*
	(0.000)	(3.100)	(1.880)
Male	0.05	–0.34	0.28
	(0.210)	(1.150)	(0.820)
Constant	0.09	–2.87***	–3.43***
	(0.160)	(3.700)	(4.080)
Observation	312	238	347
# of ones	131	118	55
Pseudo R-squared Adj	0.02	0.03	0.00
AUROC insample	0.68	0.71	0.7
AUROC outsample	0.61	0.67	0.59

Absolute value of z statistics in parentheses

*significant at 10 %;**significant at 5 %;***significant at 1 %

AUROC could very well be due to over-fitting, given the large number of explanatory variables compared to the sample size, particularly the number of bads. Over-fitting of this kind is a common concern in credit models seeking to predict default. However, it can be checked by bank decision-makers by building the model on a randomly selected subset of the data and then testing it "out-of-sample" on the remaining observations (also known as cross-validation or bootstrapping, hold-out sample, etc.). This out-of-sample process is a standard approach in credit modeling and is more suggestive of the predictive power of a credit-scoring model in implementation, when used on data that was not used to build the model.

The results applying this approach on the default outcome are shown above for banks 1–4, building the model on a randomly selected 80 % of the sample and then testing its predictive power on the remaining 20 % of the sample. Banks 5 and 6 do not have a sufficiently large sample to have a separate build and hold-out sample (Table 4.5).

Performing a regression in a random 80 % of the sample and testing on the remaining 20 % hold-out sample, we can see that the drop in AUROC of the credit-scoring model is in the range of 0.05–0.11 points, or 19 % to 55 %. Not surprisingly, the greatest drop-off in predictive power, and therefore the greatest difficulty with over-fitting of the model, is in bank 3, which has the smallest sample in terms of number of bads. Unfortunately small samples and over-fitting are a critical difficulty with attempting to use credit scoring with psychometric variables, much more than in traditional credit scoring. This empirical challenge is taken up in the following—final—chapter.

Overcoming Over-fitting in Small Sample Sizes

The results above are based on either "OLS" (ordinary least squares) or logit (binary dependent variable) regressions pooling together multiple countries, or else regressions for individual countries, using the psychometric indices resulting from the longer set of items. Logit regressions are the typical approach to building selection models (particularly for credit screening, with a binary dependent variable, i.e., default or not) but suffer from a number of shortcomings in this application of psychometrics to credit scoring, due primarily to sample size.

Traditional credit scoring in both developed and emerging markets is done using archival application data from years (and years) of past clients. But selection based on psychometric tools requires gathering additional new information. This is because unlike building a model based on typical sociodemographic characteristics like age or gender, psychometric questions have not been asked on past applications and therefore represent new data that must be collected. This prospective aspect of psychological testing is a challenge, particularly for reaching a sufficient number of bads for credit scoring (we have to wait for people to fail). There are two approaches that could be taken to collect this "future" information: administering the new application to samples of existing clients and comparing it to their repayment history (as was done here) or administering the new application to new applicants and comparing it to their subsequent repayment performance.

Bads make up a small percentage the overall client pool of most financial institutions (at least those that stay in business long enough to build credit-scoring model); therefore, if collecting data on new applicants, a very large number of tests must be tested before reaching sufficient bads in the ultimate sample. For example, if a minimum of 200 bads are needed and the typical default rate for new clients is 4 %, this requires testing 5,000 new applicants. Depending on the flow of new applications, this could take a significant amount of time, added to which is the time needed to wait for these 5,000 loans to mature and the need to apply the length test to the applicants without any immediate benefits to either them or the bank.

The alternative approach of testing existing clients has some advantages. First, unlike the case of testing new applicants, for existing clients the bads can be identified and over-sampled, as was done in this study. Instead of testing 5,000 new applicants to reach 200 bads, one could stratify and sample 200 bads and 200 goods, minimizing the effort to gather data. Moreover, using past repayment performance means the data can be analyzed as soon as it is collected, rather than waiting until the loans mature. But the downside to this approach is that defaulting clients have a fractured relationship with the financial institution, may be subject to collections and legal action by the bank, and are therefore less likely to agree to participate by completing the application.

Therefore, in attempting to create credit-scoring models based on newly collected data like psychometrics or any other nontraditional questions, there will always be downward pressure on sample size. And small samples as we have seen already are problematic because the large number of explanatory variables and small number of observations results in low statistical power and over-fitting. In the previous chapter we saw over-fitting to a significant degree, with AUROC falling by 0.05 to 0.11 points going from in-sample to out-of-sample. This over-fitting (a statistical artifact) is a major problem, as generating out-of-sample predictive power is what is required to generate increased access to finance for SMEs and stimulating economic growth in emerging markets.

To accomplish consequential validity under the traditional logit setup, the only option is to increase sample size. Pooling together data across multiple countries and market segments, as was done in the analysis above, is one way to overcome this challenge. It can improve predictive power due to more precise estimates of coefficients thanks to a larger sample size. However, this pooling of data across countries and markets comes at a cost. As shown above, some psychometric dimensions have relationships with entrepreneurial outcomes that are relatively generic: They hold across countries as different as Kenya, Colombia, South Africa, and Peru; across market segments as different as large formal small- and medium-sized enterprises and small-scale informal micro-enterprises; and across different financial institutions with their own particularities in terms of market segments, products, and procedures. But it is also clear from the results above that customizing the predictive models to the country and market could lead to further increases in the predictive power of credit-scoring models, if the problem of over-fitting can be overcome.

An Innovative Approach

We suggest an alternative modeling methodology that is better suited to these unique challenges of building credit-scoring models with smaller sample sizes, large numbers of covariates, and cross-organizational as well as cross-country datasets (hierarchical, multilevels). This approach uses a Bayesian hierarchical logit model. At the lowest level, the model is similar to a classical logit but with more flexibility than is traditionally allowed. The Appendix includes the precise model specification. Intuitively, the model assumes that the outcome varies by country and by market segment within each country and that the relationship between covariates and the outcome varies by organization. The approach is therefore inherently multilevel.

Table 4.6 AUROC by Bank: in-sample versus out-of-sample

		Bank1	Bank2	Bank3
Traditional logit	In sample	0.68	0.71	0.7
	Out of sample	0.61	0.67	0.59
	Decrease	0.07	0.04	0.11
Bayesian hierarchical logit	In sample	0.64	0.63	0.66
	Out of sample	0.62	0.62	0.63
	Decrease	0.02	0.01	0.03

To allow these levels of flexibility, the hierarchical model imposes a second-level prior on the unknown parameters. This second-level prior probability expectation shares information across parameters, depending on the amount of information available from different sources. For instance, in the final equation, the estimated item-level effect is a weighted combination of the average global effect and the effect estimated from the data available at a particular country and segment. As more data arrives, more weight is placed on the latter. Likewise, the prior on coefficients shrinks the estimate effects towards a common effect estimated for all coefficients. The hierarchical model partially pools information to avoid over-fitting the relatively large number of explanatory variables to the relatively small number of tests.

Moreover, to balance between a country-specific (local) and global model, the second-level prior assumes each coefficient comes from a common distribution across countries. This allows the model to smoothly customize from a global model to a country- and market-specific model as data arrives, capturing the psychometric uniqueness of different countries and banks. The rate of this transition depends on the estimated similarity in the model across countries and the available data. For items that behave similarly across countries, the global model, which pools all information and is therefore more precisely estimated, dominates. But for covariates with significant heterogeneity across countries, the country-specific coefficient begins to dominate quickly as data arrives. This partial pooling of country-specific data with a global model of default risk is a central benefit of Bayesian models and improves hold-out sample predictive performance, particularly when limited arrears data is available for new implementing countries. Table 4.6 above compares the results of the two approaches.

The fall in predictive power from in-sample to out-of-sample under a traditional logit ranges from .04 to .11 AUROC points, due to over-fitting. But in a Bayesian hierarchical logit, the decrease is significantly smaller, only .01 to .03 AUROC points. More important though than the decrease is simply the absolute level of the out-of-sample AUROC.

This is what a lender will care about when deciding if a credit scorecard is valuable and sufficient to increase lending to SMEs. In two of the three banks, the out-of-sample AUROC is higher under the Bayesian model, but in bank 2 this is not the case.

This differential validity is suggestive that the Bayesian hierarchical logit is superior, but more testing is needed across a larger set of samples before this can be stated conclusively. But if the global–local approach can be further refined and validated, it could ameliorate one of the major barriers to using newly collected information, such as psychometrics, in credit scoring: over-fitting in small samples and the challenges of sharing information across markets. Resolving this problem would help pave the way for new models to incorporate newly collected data like psychometrics and thereby rapidly enhances lenders' abilities to evaluate risk and lend to underfinanced SMEs.

Chapter 5
Conclusion

Abstract While these current and potential entrepreneurs face numerous hurdles, the evidence clearly shows that the difficulties of financial intermediation for small and medium-sized enterprises are both significant and costly. Overcoming this barrier represents both a major profit opportunity for lenders and a major development opportunity for society at large, including of course entrepreneurs themselves. New tools that allow for screening and risk evaluation for small and medium-sized enterprises with low transaction costs and without depending on pre-existing information like borrowing history or business plans could represent a breakthrough in solving this problem. We have proposed one such tool, the use of psychometric tests, and evaluated its potential both conceptually, based on past studies, and based on a newly collected international dataset. The results show that there are some psychometric dimensions that have statistically and economically significant relationships with business profitability, which is of significant interest to investors, entrepreneurs, and capacity builders, and also that have significant relationships with default risk, which is of significant interest to lenders. Some of them are found to hold with surprising stability across a wide variety of countries, cultures, and business types. These questions could provide the boost to predictive power needed to bring millions of striving small business owners into the formal financial system and give them the capital they need to grow their businesses, if they can be successfully leveraged for credit screening. The Entrepreneurial Finance Lab (or EFL for short) is a company set up to work with banks to deploy this technology and realize this potential. Since 2010, the company has been implementing a credit-screening tool including psychometric content similar to that reviewed above, and modeled using the Bayesian hierarchical methodology.

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Promoting economic growth and poverty reduction in emerging markets is one of the key challenges facing society today. Unleashing the latent entrepreneurial potential in these markets is one of the best ways to ensure this challenge is met in a significant and sustainable way. While these current and potential entrepreneurs face numerous hurdles, the evidence clearly shows that the difficulties of financial intermediation for small- and medium-sized enterprises are both significant and costly. Overcoming this barrier represents both a major profit opportunity for lenders and a major development opportunity for society at large, including of course entrepreneurs themselves.

New tools that allow for screening and risk evaluation for small- and medium-sized enterprises with low transaction costs and without depending on pre-existing information like borrowing history or business plans could represent a breakthrough in solving this problem. We have proposed one such tool, the use of psychometric tests, and evaluated its potential both conceptually, based on past studies and based on a newly collected international dataset. The results show that there are some psychometric dimensions that have statistically and economically significant relationships with business profitability, which is of significant interest to investors, entrepreneurs, and capacity builders, and also that have significant relationships with default risk, which is of significant interest to lenders. Some of them are found to hold with surprising stability across a wide variety of countries, cultures, and business types. These questions could provide the boost to predictive power needed to bring millions of striving small business owners into the formal financial system and give them the capital they need to grow their businesses, if they can be successfully leveraged for credit screening.

Implications for Practice: The Entrepreneurial Finance Lab

The Entrepreneurial Finance Lab (or EFL for short) is a company setup to work with banks to deploy this technology and realize this potential. Since 2010, the company has been implementing a credit-screening tool including psychometric content similar to that reviewed above and modeled using the Bayesian hierarchical methodology.

As of the end of 2012, this tool is being used in countries across Latin America, Asia, and Africa, with over 48,000 applications completed. Using this application, EFL's partner banks have originated over $170 million US dollars to small businesses, over two thirds of which would have been rejected by traditional underwriting criteria. Though still in pilot phases, these implementations have been highly profitable for the financial institutions, leading to rapid scale-up across the globe. And the success stories of the entrepreneurs that have benefitted from this tool show the power of productive finance in improving lives.

Leah Mugure Mwaura Story

Photo is courtesy of Greg Larson

Leah Mugure Mwaura sells mutumba, or second-hand clothing, in Gikomba market in Nairobi, Kenya. She first opened her shop in 1991 with 15,000 shillings (approximately $170 USD). Her husband, an accountant during the 1990s, told Leah that banks were only giving loans to "big big people" or big companies, so for 19 years she ran her business without a bank loan. She said: "for twenty years I was running it by myself!! With my own money… No help, there was no help." She took small assistance from group loans, and once she approached a bank because she needed 500,000 shillings ($5,500) in capital, but after an initial consultation where they looked at her turnover, the maximum they offered her was 100,000($1,100)—provided that she could provide collateral and a guarantor. "I was despairing. I did away with banks" she recalls. She walked away and never went back to the bank.

In 2010, Leah took the EFL application and was approved for an unsecured 600,000 shilling loan. She recalls: "I expected it to take a month or two and so I was surprised to get it in 2 weeks´ time. There was no struggle. I was not told 'go see so and so.' I was just referred to one person. I'm happy with that bank … you feel wanted. I've even introduced some friends to be customers there."

When she received the loan she put it towards her business "you will get bigger profits … like with the loan I got: if I had used it to buy a car or a house, surely I would not be where I am now. But I put that loan, 100 % of it, in here. And I've seen the profits." She paid back her first loan, and her second loan from the bank was more than tripled: A 2M shilling loan last November. And she now has a new shop to accommodate the extra bales. Even though business has been slow this month, she's happy and comfortable saying, "I can pay! That's why I don't even look stressed. I have stock… I'm not stressed because I know I'll manage to pay the loan. The value of my stock is more than the loan that I'm having." She's looking forward to more loans, and more expansion adding, "I even want to expand more — and take the position of my supplier! I'll be his competitor. You know, you have to think big."

"I have really made it in Gikomba, and I'm really proud of the place. If I imagine for the 19 years I started with a capital of 15,000 shillings… I never even dreamt of dealing with millions of shillings… So I can say that I'm proud – it has moved me from point A to C … The loan has helped me. To be sincere it has tripled my business. And I expect to do better after finishing this current loan."

Implications for Future Research

The results reviewed in this study overcome many weaknesses of previous research, often based on conveniently available samples of entrepreneurs in rich countries without clear and comparable performance data. The dataset is large compared to some studies and more importantly is from emerging rather than developed countries, actually from a variety of emerging countries, providing both a more relevant sample and richer cross-cultural heterogeneity. Equally important, the results are based on a relatively clear and consistent set of tests and outcome variables, including actual loan repayment performance, which is a first in the literature. Finally, an alternative modeling methodology based on Bayesian techniques was introduced that is more robust to what will be an ever-present challenge to the application of psychometrics to credit scoring, namely, small samples sizes with cross-country data.

However, there are some weaknesses that should be overcome in new work. Most critical is the issue of external validity. As the goal is to evaluate the power of these tools when implemented in a high-stakes setting with real bank loans on the line, the evaluation of their power should be under as similar circumstances as possible. This means that the stakes should be high, with test-takers putting in full effort and attention, and even attempting to game or "beat" the test. That is the truest validation of how well such a tool would function in practice. It also means that testing should be performed prior to the success or failure of the business or success or failure at repaying the loan, to eliminate possibilities of reverse causality.

That setup would also allow for an extension of the psychometric factors considered herein to include other dimensions that could have an even stronger relationship with entrepreneurial outcomes but are potentially more malleable and less stable over time. Such factors had to be ignored in this retrospective study but could have strong relationships with default risk. Even more interestingly, they would allow for direct studies of the causal impact of educational and public policies to "improve" those malleable characteristics on business success, which is of primary interest to capacity builders and policy-makers seeking to encourage more and better entrepreneurial activity in their countries.

Future work will therefore prioritize ex ante high-stakes data collection, from even larger samples across a wider variety of emerging markets. If those results continue to validate the added value of psychometric content to credit applications for small business borrowers, the impact on employment, GDP growth, and entrepreneurship in emerging markets would be enormous. It would help the hundreds of millions of entrepreneurs currently locked out of the formal credit system achieve greater business success, become profitable clients for banks, and further contribute to economic growth and job creation in their communities.

Florence Atieno Ahenda Story

Photo is courtesy of Greg Larson

Florence Atieno Ahenda is a wholesale used shoe-seller with a stall located on a busy corner in Gikomba Market in Nairobi, Kenya. Ten years ago, Florence started the business with nothing. As the years passed, it grew "slowly by slowly," but at some point, sales plateaued. She normally purchased a stock supply of about five bales of shoes—or about $750 in inventory. She would work on selling those shoes until she raised another $750 and then buy more stock. But she could never seem to expand beyond the sell-and-restock cycle. Florence never had a bank loan; she never even opened an account. The business operated on cash savings, and Florence never imagined that she could get approved for a loan. "Not in my wildest dreams," she says.

Meanwhile, Florence was raising a family almost completely on her own. Her husband was laid off in 2001 and in order to sustain her family she began selling shoes in Gikomba that same year. Her husband never found another job, forcing Florence to be the family's sole breadwinner.

In 2010, Florence saw ads around Gikomba for a new bank branch. She decided to open up an account—her first ever—and the teller mentioned their new small business loans, with the EFL Application process that involved no guarantors or collateral and featured a set of new nontraditional questions on a touch screen computer. Despite having zero banking history, Florence took the application and was approved for a first-time unsecured loan of $6,000. She was ecstatic and determined to stay in good standing with the bank.

Florence paid off that first loan six months early. The bank pre-approved her for a second loan of $12,000; when she paid that loan back on time, the bank approved her for a third loan, of $24,000, which she is currently servicing and is on track to pay off on time. All told: Over two and a half years, Florence accessed $42,000 in unsecured loans to expand her wholesale shoe business. The impact, both on Florence's shoe shop and her family, has been remarkable.

Nowadays, Florence's stock supply is fifty bales of shoes—or about $7,500 in inventory, a tenfold improvement in just a few years. Her sales cycle has improved dramatically, as well; whereas it used to take more than a week to sell her small inventory, she now moves fifty bales of product in less than five days, on average. With her third loan, Florence has moved up the supply chain in Gikomba.

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The new capital was enough to make a down payment on a large consignment in Germany. She's now an intermediary supplier, but her dream is "to become the supplier of the suppliers."

Today, Florence is proud. Her business is thriving, and her children are excelling in school—she never dreamed she'd be able to pay for her kids to attend university. She credits her family's good fortune to the success of her business in Gikomba she says: "Good life! We are truly having the good life. I feel good because now I have money—I can boost my business right, and I can educate my children."

It is no coincidence that each of these case studies is about a female entrepreneur. The previously mentioned microfinance "ghetto" for women entrepreneurs is just one symptom of lending selection criteria that often are even more difficult for women. For example, in some countries, it is more difficult if not impossible for women to pledge household assets as collateral, which makes a collateral requirement systematically discouraging to female entrepreneurs for their applying to get and ever obtaining larger amounts of credit. Women entrepreneurs are more likely to face higher interest rates, are required to collateralize a greater percentage of their loan, and have shorter loan terms than men (IFC 2011).

In the regions EFL has a larger geographical footprint, such as Latin America and sub-Saharan Africa, women encounter particularly strong biases. For very small businesses in Latin America (those that employ 5–9 people), 57–70 % of women-owned firms either need loans and were rejected by a bank or need larger loans, compared to 50–61 % of men-owned business (IFC 2011). Across Latin America, women are approximately 14 % less likely than men to have a bank loan or line of credit and are required to have approximately 8.1 % more collateral than men for bank loans (World Bank 2012). In sub-Saharan Africa for those that received loans, the average loan size indexed to revenue was 13 % to 16 % for women versus 17 % to 21 % for men (IFC 2011).

EFL's tool enables bank lending to female entrepreneurs by eliminating gender biases and helping banks lend to the informal small- and medium-sized enterprise sector. By using the responses to the application in place of traditional requirements, EFL's partner banks have closed this gender gap, as the data shows equal approval rates for male and female applicants, with nearly identical terms applied to the resulting loans. In fact, one EFL partner bank stated, "in the past 18 months, we have been able to offer access to finance to unbanked and underserved SMEs across Africa by applying the EFL Tool. Half of the beneficiaries are women and many have successfully repaid their first loan and qualified for additional facilities." In general, EFL's partner banks have increased the percentage of women-owned SMEs they lend to by over 70 %, translating into over $45 million dollars of additional lending.

EFL Story

For banks, the EFL credit-scoring tool has allowed them to both help fuel the growth of their local economy and grow their loan portfolios with quality. As one partner bank said: "the key driver of growth in most emerging markets around the world is Small & Medium Enterprises…[yet] many small business owners continually tell us that the one aspect that constraints their growth is access to finance. We have found a solution to meet our customer's needs, by using it we can give many of them the opportunity of growing their businesses. Through a capability introduced to us by the Entrepreneurial Financial Laboratory (EFL) we now have a tool to assist us is making speedy lending decisions."

As another partner described how using EFL's "nontraditional toolset" to evaluate entrepreneurs has allowed them to accept more loan applicants by "cut[ing] through the red tape we traditionally required for lending to this segment, and allowed a shorter, more convenient customer experience" without increasing the risk of their portfolios. As our partner continued to say, "the end result has been a completely revolutionary approach of determining the willingness of the client to pay back debt and also their ability to manage their business which can enable banks to enhance traditional scorecard building techniques to become even more predictive."

For more information about the Entrepreneurial Finance Lab, please visit www.eflglobal.com. Though this organization is the leader in applying psychometrics to credit risk modeling, it is our hope that with additional results and impact, other organizations will experiment with nontraditional data, including psychometrics, to further enable SME lending and unleash the entrepreneurial potential that is currently held back in emerging markets due to barriers to productive lending.

The final chapter discusses implications of these results for future research, both academic and applied.

References

Almlund, M., Duckworth, A., Heckman, J., & Kautz, T. (2011). *Personality psychology and economics*. Cambridge, MA: National Bureau of Economic Research working paper 16822.

American Management Association. (2001). *2001 AMA survey on workplace testing: basic skills, job skills, and psychological measurement*. New York: American Management Association.

Asch, L. (2000). Credit scoring: a tool for more efficient SME lending. *SME Issues*, *1*(2), 1–4, World Bank Group.

Banerjee, A., & Duflo, E. (2002). *Do firms want to borrow more? Testing credit constraints using a directed lending program*. MIT department of economics working paper 02–25.

Barrick, M., & Mount, M. (1991). The Big Five personality dimensions and job performance: a meta-analysis. *Personnel Psychology, 44*, 1–26.

Bernardin, H., & Cooke, D. (1993). Validity of an honesty test in predicting theft among convenience store employees. *The Academy of Management Journal, 36*(5), 1097–1108.

Cable, D., & Shane, S. (1997). A prisoner's dilemma approach to entrepreneur-venture capitalist relationships. *Academy of Management Review, 22*(1), 142–176.

Caliendo, M., & Kritikos, A. (2012). Searching for the entrepreneurial personality: new evidence and avenues for further research. *Journal of Economic Psychology (Special Issue Editorial), 33*(2), 319–324.

Chell, E. (2008). *The entrepreneurial personality: a social construction*. London: Routledge.

Ciavarella, M., Buchholtz, A., Riordan, C., Gatewood, R., & Stokes, G. (2004). The Big Five and venture survival: Is there a linkage? *Journal of Business Venturing, 19*, 465–483.

Costa, P., & McCrae, R. (1994). The stability of personality: observations and evaluations. *American Psychological Society, 3*(6), 173–175.

De Mel, S., McKenzie, D., & Woodruff, C. (2008). Returns to capital in microenterprises: evidence from a field experiment. *The Quarterly Journal of Economics, 123*(4), 1329–1372.

De Mel, S., McKenzie, D., & Woodruff, C. (2010). Who are the microenterprise owners? Evidence from Sri Lanka on Tokman versus De Soto. In J. Lerner & A. Schoar (Eds.), *International differences in entrepreneurship* (pp. 63–87). Chicago, IL: University of Chicago Press.

Djankov, S., Miguel, E., Qian, Y., Roland, G., & Zhuravskaya, E. (2005). Who are Russia's entrepreneurs? *Journal of the European Economic Association, 3*(2–3), 587–597.

Djankov, S., Qian, Y., Roland, G., & Zhuravskaya, E. (2007). *What makes a successful entrepreneur? Evidence from Brazil*. Russia: Center for Economic and Financial Research Working Paper 0104.

B. Klinger et al., *Enterprising Psychometrics and Poverty Reduction*,
SpringerBriefs in Psychology: SpringerBriefs in Innovations in Poverty Reduction,
DOI 10.1007/978-1-4614-7227-8,

FOMIN [Fondo multilateral de inversiones]. (2011). *Banks and SMEs: raising the game. 4th regional survey in Latin America and the Caribbean*. Mimeo: Inter-American Development Bank.

Gartner, W. (1989). 'Who is an entrepreneur?' Is the wrong question. *Entrepreneurship Theory and Practice, 12*(2), 47–68.

Gelman, A., Carlin, J., Stern, H., & Rubin, D. (2003). *Bayesian data analysis* (2nd ed.). London: Chapman & Hall/CRC.

Glaub, M., Fischer, S., Klemm, M., & Frese, M. (forthcoming). *A theory-based controlled randomized field intervention: increasing proactive behavior (personal initiative) in small business owners leads to entrepreneurial success*. Mimeo.

Gottfredson, G., Jones, E., & Holland, J. (1993). Personality and vocational interests: the relation of Holland's size interest dimensions to five robust dimensions of personality. *Journal of Counseling Psychology, 40*, 518–524.

Handler, C. (2008, May). Results from 5th annual rocket-hire online screening and assessment usage survey. *Journal of Corporate Recruiting Leadership 3*, (6).

Hausman, R., Rodrik, D., & Velasco, A. (2005). *Growth diagnostics*. Boston, MA: Harvard University.

Hogan, R. (1991). Personality and personality measurement. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (Vol. 2, pp. 873–919). Palo Alto, CA: Consulting Psychologists Press.

Holland, J. (1985). Making vocational choices. *A theory on vocational personalities and work environments*. Englewood Cliffs, NJ: Prentice-Hall.

Hough, L. M., Eaton, N. K., Dunnette, M. D., Kamp, J. D., & McCloy, R. (1990). Criterion-related validities of personality constructs and the effect of response distortion on those validities. *Journal of Applied Psychology, 75*, 581–595.

IFC [International Finance Corporation]. (2011). *Strengthening access to finance for women-owned SMEs in developing countries*. Washington DC: IFC global partnership for financial inclusion.

Ivory, B. (2003). Poverty and enterprise. In S. C. Carr & T. S. Sloan (Eds.), *Poverty and psychology: from global perspective to local practice* (pp. 251–266). New York: Springer.

Judge, T., Higgins, C., Thoresen, C., & Barrick, M. (1999). The Big Five personality traits, general mental ability, and career success across the life span. *Personnel Psychology, 52*(3), 621–652.

McClelland, D. (1961). *The achieving society*. Princeton, NJ: Van Nostrand.

Mester, L. (1997). What's the point of credit scoring? *Federal Reserve Bank of Philadelphia's Business Review (September/October)*, 3–16.

Rauch, A., & Frese, M. (2007). Let's put the person back into entrepreneurship research: a meta-analysis on the relationship between business owners' personality traits, business creation and success. *European Journal of Work and Organizational Psychology, 16*(4), 353–385.

Schmeichel, B., Vohs, K., & Baumeister, R. (2003). Intellectual performance and ego depletion: role of the self in logical reasoning and other information processing. *Journal of Personality and Social Psychology, 85*, 33–46.

Schmidt, F., & Hunter, J. (1998). The validity and utility of selection methods in personnel psychology: practical and theoretical implications of 85 years of research findings. *Psychological Bulletin, 124*(2), 262–274.

Schmitt, D., Allik, J., McCrae, R., & Benet-Martinez, V. (2007). The geographic distribution of big five personality traits. *Journal of Cross-cultural Psychology, 28*(2), 173–212.

Schweizer, K., Goldhammer, F., Rauch, W., & Moosbrugger, H. (2007). On the validity of Raven's matrices test: does spatial ability contribute to performance? *Personality and Individual Differences, 43*, 1998–2010.

Shane, S. (2010). *The illusions of entrepreneurship: the costly myths that entrepreneurs, investors and policy makers live by*. Yale, CT: Yale University Press.

Shaver, K. (1995). The entrepreneurial personality myth. *Business & Economic Review, 41*(30), 20–23.

Shaver, K. (2007). C2D2: Psychological methods in entrepreneurship research. In J. Baum, M. Frese, & R. Baron (Eds.), *The psychology of entrepreneurship*. Mahwah, NJ: Lawrence Erlbaum Associates.

Spearman, C. (1946). Theory of the general factor. *British Journal of Psychology, 36*, 117–131.
Stein, P., Goland, T., & Schiff, R. (2010, Oct). Two trillion and counting: assessing the credit gap for micro, small and medium-size enterprises in the developing world. Mimeo: International Finance Corporation and McKinsey & Company.
Van Iddekinge, C., Roth, P., Raymark, P., & Odle-Dusseau, H. (2012). The criterion-related validity of integrity tests: an updated meta-analysis. *Journal of Applied Psychology, 97*, 499–530.
World Bank. (2012). *Enterprise surveys*. www.enterprisesurveys.org. Accessed Nov 2012.
Zhao, H., & Seibert, S. (2006). The Big Five personality dimensions and entrepreneurial status: a meta-analytical review. *Journal of Applied Psychology, 91*(2), 259–271.
Zuckerman, S. (1996). Taking small business competition nationwide. *United States Banker, 106–8*(August), 24–28.

Appendices

Appendix 1 Detailed Bayesian Specification

Let y_i be a binary variable indicating whether loan i is in arrears for a specified period, for instance, more than 90 days. As in a logit model, the probability of default p_i and observed default y_i are modeled as a random process as follows:

$$p_i = \text{logit}^{-1}(\alpha_{\text{partner[i]}} + \gamma_{\text{branch[i]}} + \sum_{j=1}^{J} \mathbf{x}_{\text{ij}}^{t} \beta_{\text{j, partner[i]}})$$

$$y_i \sim \text{Bernoulli}(p_i)$$

This model is a mixed, or varying-intercept and varying-slope, logit. The probability of default depends on a partner and branch effect, α_c and γ_b, and J sets of controls, indexed by j, whose relationship with default risk, β_{jc}, varies by partner c.

Because both the slopes and intercepts of the model vary across partners and because of the large number of covariates, the number of unknown parameters is large relative to the available data. Estimating this model using classical methods, such a marginal maximum likelihood, would therefore significantly overfit the data. To address this, the EFL model uses a hierarchical prior and Bayesian estimation to impose a structure on the parameters that borrows information across partners and covariates.

The EFL Hierarchical Logit includes a level-2 model:

$$\alpha_c \sim N(\mu_\alpha, \tau_\alpha)$$

$$\gamma_b \sim N(0, \tau_\gamma)$$

$$\beta_{jkc} \sim N(\mu_{\beta jk}, \tau_{\beta j})$$

$$\mu_{\beta jk} \sim N(\lambda_j, \eta_j)$$

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The model is completed with independent, weakly informative, Normal and Inverse-Gamma priors on the remaining parameters, μ_α, τ_α, τ_γ, $\tau_{\beta j}$, λ_j, and η_j.

This hierarchical structure has several key features. The τ_α and τ_γ precision parameters capture how similar partners and branches are in terms of average default risk. They govern how quickly high default rates for a particular partner or branch will outweigh the global estimates of default risk. Next, $\mu_{\beta jk}$ captures the global effect of variable k in group j on default risk. While the actual effect, β_{jkc}, varies by partner c, the global effect does not. The global effect dominates when limited information is available at the partner level. As data arrives, the model specializes to better fit the partner but balances this specialization with global information. The rate of transition is governed by $\tau_{\beta j}$, which captures how much variation across countries is typical for covariates in group j. Finally, λ_j and η_j govern how much variation there is across coefficients of particular type j. If the global precision η_j is large, then item-level responses are strongly shrunk towards the common effect λ_j. This allows the use of item-level data rather than arbitrary aggregates, while guarding against over fitting. All these parameters, except the topmost prior parameters, can be estimated from the data using Bayesian methods.

The primary goal is to estimate the default risk p_i. This is captured by posterior distribution of default risk, $p\left(p_i \mid y, \mathbf{X}\right)$, which integrates over all unknown parameters and conditions on the observed data. Given the model above, the posterior distribution is

$$p\left(p_i \mid \mathbf{y}, \mathbf{X}\right) \propto \int \operatorname{logit}^{-1}\left(\alpha_{\text{partner[i]}} + \gamma_{\text{branch[i]}} + \sum_{\text{j}=1}^{J} \mathbf{x}_{ij}^{t} \beta_{\text{j, partner[i]}}\right)$$

$$\cdot \prod_{i=1}^{N} p\left(y_i \mid \mathbf{X}_{\text{i,}} \alpha_{\text{partner[i],}} \gamma_{\text{branch[i],}} \beta_{\text{partner[i]}}\right) \cdot \prod_{c=1}^{C} p\left(\alpha_c \mid \mu_\alpha, \tau_\alpha\right) \cdot \prod_{b=1}^{B} p(\gamma_b \mid \tau_\gamma)$$

$$\cdot \prod_{j=1}^{J} \prod_{k=1}^{K_j} \prod_{c=1}^{C} p\left(\beta_{jkc} \mid \mu_{\beta jk}, \tau_{\beta j}\right) \cdot \prod_{j=1}^{J} \prod_{k=1}^{K_j} p\left(\mu_{\beta jk} \mid \lambda_j, \eta_j\right) p\left(\mu_\alpha, \tau_\alpha, \tau_\lambda, \tau_{\beta j}, \lambda_j, \eta_j\right) d\theta$$

which follows from Bayes rule and basic rules of probability. This model can be estimated using Markov Chain Monte Carlo methods (see, for example, Gelman et al. 2003).

Appendix 2

Variable	Partner	Min	Max	P5	P50	P95	Mean	S.D
Neuroticism (–)	Bank1	−1.70	2.41	−1.70	−0.33	1.04	−0.41	0.85
	Bank2	−1.70	1.95	−1.70	0.12	1.49	0.02	0.91
	Bank3	−1.70	2.41	−1.24	−0.33	1.49	−0.02	0.94
	Bank4	−1.70	2.41	−1.24	0.58	2.18	0.50	1.03
	Bank5	−1.70	1.95	−1.24	0.12	1.49	0.18	0.90
	Bank6	−1.70	3.32	−1.70	−0.33	1.49	−0.09	1.03
Extroversion	Bank1	−2.91	1.46	−1.66	0.00	1.04	−0.11	0.84
	Bank2	−2.91	1.66	−1.66	0.31	1.46	0.14	0.92
	Bank3	−3.33	1.46	−2.08	−0.42	1.04	−0.43	0.96
	Bank4	−2.50	1.66	−1.04	0.83	1.46	0.51	0.90
	Bank5	−2.08	1.66	−1.25	0.42	1.46	0.35	0.79
	Bank6	−3.33	1.66	−1.66	0.21	1.25	−0.03	0.91
Openness	Bank1	−3.02	1.22	−1.20	0.01	1.22	0.06	0.91
	Bank2	−3.02	1.22	−1.20	0.01	1.22	0.18	0.78
	Bank3	−2.41	1.22	−1.81	0.01	1.22	−0.26	1.00
	Bank4	−3.02	1.22	−1.50	0.01	1.22	0.12	0.85
	Bank5	−1.81	1.22	−1.81	0.01	1.22	0.02	0.82
	Bank6	−2.41	1.22	−1.81	−0.60	1.22	−0.45	0.93
Agreeableness	Bank1	−2.76	1.23	−1.05	0.09	1.23	0.18	0.71
	Bank2	−3.90	1.23	−1.62	0.09	1.23	−0.17	0.83
	Bank3	−3.33	1.23	−1.62	0.09	1.23	−0.03	0.86
	Bank4	−2.76	1.23	−1.62	0.09	1.23	−0.23	0.79
	Bank5	−2.19	1.23	−1.62	0.09	0.66	−0.20	0.64
	Bank6	−2.19	5.22	−1.62	0.09	1.23	0.23	0.98
Conscientiousness	Bank1	−2.64	1.96	−1.11	0.42	1.19	0.21	0.77
	Bank2	−2.90	2.47	−1.62	−0.09	1.70	0.03	1.00
	Bank3	−3.15	2.21	−1.88	−0.34	1.45	−0.25	0.98
	Bank4	−3.41	1.96	−1.88	−0.09	1.45	−0.07	1.02
	Bank5	−2.13	1.96	−1.11	0.17	1.19	0.10	0.74
	Bank6	−3.67	2.21	−1.88	−0.09	1.70	0.05	1.13
Integrity	Bank1	−1.62	2.37	−0.94	0.09	1.25	0.10	0.70
	Bank2	−2.39	2.37	−2.20	−0.40	1.64	−0.31	1.19
	Bank3	−2.30	2.37	−1.32	0.23	1.88	0.21	0.96
	Bank4	−2.05	2.37	−1.42	−0.06	1.88	0.11	1.02
	Bank5	−2.20	2.37	−1.57	−0.06	1.88	−0.03	1.05
	Bank6	−2.20	2.37	−1.17	−0.25	1.45	−0.14	0.97
Digit span	Bank1	1	12	2	5	7	4.47	1.57
	Bank2	1	13	1	5	9	4.81	2.27
	Bank3	1	13	1	5	8	4.27	1.96
	Bank4	1	12	1	6	9	5.59	2.09
	Bank5	1	10	2	6	9	5.48	1.99
	Bank6	1	9	2	5	8	4.88	1.55
Ravens	Bank1	−1.14	2.54	−1.14	0.24	1.62	0.19	0.84
	Bank2	−1.14	3.46	−1.14	0.24	1.62	0.19	0.93
	Bank3	−1.14	2.08	−1.14	−1.14	0.70	−0.95	0.57
	Bank4	−1.14	3.00	−1.14	0.24	2.08	0.44	1.13
	Bank5	−1.14	2.54	−1.14	0.24	2.08	0.37	0.95
	Bank6	−1.14	2.08	−1.14	0.24	1.62	0.34	0.89

	Bank 4		Bank 5		Bank 6	
Model	OLS	Logit	OLS	Logit	OLS	Logit
Dependent var	LN Business profits in US dollars	Default	LN Business profits in US dollars	Default	LN Business profits in US dollars	Default
Neuroticism (–)						–1.59***
						(3.260)
Extroversion						0.95**
						(1.960)
Openness						–0.73*
						(1.930)
Agreeableness						
Conscientiousness						
Integrity				–0.70**		–1.17**
				(2.340)		(2.760)
Digit span	–0.62***			0.54*		–0.86*
	(3.610)			(1.920)		(1.770)
Ravens	0.54**	–0.53	0.36**			1.19***
	(2.580)	(1.500)	(2.340)			(2.840)
Age (cohorts)						
Education	–0.58**					
	(2.390)					
Male	–0.53				0.33*	
	(1.500)				(1.790)	
Constant	3.28**	–2.15***	0.64***	–1.40***	0.09	–3.05***
	(4.140)	(6.280)	(4.260)	(4.120)	(0.680)	(4.890)
Observations	29	137	47	74	102	103
# of ones		11		20		20
R-squared	0.44		0.11		0.03	
P seudo		–0.02		0.05		0.15
R-squared Adj						
AURO_All		0.62		0.74		0.85

Absolute value of t statistics in parentheses
* significant at 10%;** significant at 5%;*** significant at 1%