

**A HUMAN RESOURCES APPROACH TO
ENTREPRENEURSHIP: SELECTION AND
TRAINING OF SMALL-BUSINESS OWNERS IN
DEVELOPING COUNTRIES**

Der Fakultät Wirtschaftswissenschaften der Leuphana Universität

Lüneburg zur Erlangung des Grades

Doktor der Philosophie

- Dr. phil. -

vorgelegte Dissertation von

Thorsten Johannes Dlugosch

geb. 28.04.1984 in Oberndorf am Neckar

Eingereicht am: 14.05.2016

Betreuer und Gutachter: Prof. Dr. Michael Frese

Gutachter: Prof. Dr. Ute-Christine Klehe

Gutachter: Jun.-Prof. Dr. Kathrin Rosing

Tag der Disputation: 08.07.2016

ACKNOWLEDGEMENTS

I am thankful to Prof. Michael Frese for giving me the opportunity to write this dissertation. It has been an honor working on projects with you – I believe that this is the way science and research is meant to be done, and I am still fascinated by the energy and motivation you put in all this. Thank you to Prof. Ute-Christine Klehe and Jun.-Prof. Kathrin Rosing for serving as second examiners and giving me the chance to hand in this dissertation.

I have spent some joyful years throughout this dissertation, and you made this time very special to me: Kim Bischoff, Michael Gielnik, Sebastian Göse, Thomas Hansmann, Matthias Klöppner, Mona Mensmann, Hinnerk Requardt, Björn Seeger, and Miriam Stark. Thank you for the incredible journey and all the adventures we had.

Big thanks to everybody who accompanied me on my travels, especially Kay Turski, Melanie von der Lahr, Daniel Henao Zapata, and Mathias Glaub.

Regina Müller – you have always taken care of me, and I am sincerely thankful for that. Thanks as well to all my other colleagues at Leuphana University for many interesting discussions, some of them even science-related: Johann Bronstein, Sebastian Fischer, Monika Lesner, Masiar Nashat, Katrin Obermeit, Adalbert Pakura, and Christoph Seckler.

Jonas Thielemann – I miss you, and I will keep your memory.

A huge thank you to my family, especially my mother Helga and my father Georg. You have done more for me than anyone could ever ask for, and I will try my best to live up to that. Thank you so much! I could not have done this without you.

Last, but not least, another huge thank you to Wasilena Georgieva. Thank you for supporting me, for being my light in times of darkness, for making me smile, for reminding me of the things that really matter. I love you.

“Be happy. Stand up straight for your beliefs. Remember your family.

And help people whenever you can.” (Arlen Griffey)

TABLE OF CONTENTS

CHAPTER 1	General Introduction to the Role of Selection and Training in Entrepreneurship.....	6
1.1	Selection and Training in Entrepreneurship	6
1.1.1	Selection in Entrepreneurship.....	7
1.1.2	Training in Entrepreneurship.....	9
1.2	The Conception of the Dissertation	10
CHAPTER 2	Predicting Loan Default of Small Business Borrowers using Personality Measures: Two Studies on Prediction Models in low- and high-stakes Settings in Developing Countries	11
2.1	Abstract.....	11
2.2	Theory	12
2.2.1	Faking and Response Distortion.....	17
2.2.2	The Entrepreneurial Setting.....	19
2.3	Study 1.....	21
2.3.1	Method.....	21
2.3.2	Design.....	21
2.3.3	Results	24
2.3.4	Discussion.....	28
2.4	Study 2.....	29
2.4.1	Method.....	31
2.4.2	Results	34
2.4.3	Discussion.....	41
2.5	General Discussion.....	42
2.5.1	Strengths and Limitations	44
2.5.2	Conclusion and Implications	45
CHAPTER 3	Comparing an Action-Oriented with a Knowledge-Based Training in Improving Entrepreneurial Skills in a Developing Country	47
3.1	Abstract.....	47
3.2	Introduction	47
3.3	Theory	48
3.4	Method.....	54
3.4.1	Design.....	54
3.4.2	Sample	54
3.4.3	Treatment.....	56
3.4.4	Measures	57
3.5	Results	65
3.5.1	Reaction Measures.....	65

Table of Contents

3.5.2	Learning, Behavioral & Success Measures	68
3.5.3	Mediation of PI.....	71
3.6	Discussion.....	74
3.6.1	Strengths and Limitations	79
3.6.2	Future Research	79
3.6.3	Conclusion and Implications	80
CHAPTER 4	Conclusion and General Discussion	81
References	85
Appendix	92

CHAPTER 1

General Introduction to the Role of Selection and Training in Entrepreneurship

1.1 Selection and Training in Entrepreneurship

With this dissertation, I present a human resources approach to entrepreneurship through selection and training of small-business owners in developing countries. Entrepreneurship is an important source of employment, innovation, and general economic prosperity (Autio, 2005; Walter et al., 2005; Reynolds et al., 2005; Kuratko, 2003). In developing countries, job creation through business ownership is especially important because job opportunities are limited (Walter et al., 2005; Mead & Liedholm, 1998). Strengthening the small business sector is one of the best ways to reduce poverty and increase economic growth (Birch, 1987). Thus, this dissertation adds to the scientific literature in taking a human resources approach to entrepreneurship: selecting and training entrepreneurs. Selection has widely been researched on in various scientific fields like human resource management, industrial-, work-, and organizational psychology, but only partly focusing on selection of entrepreneurs. Regarding training, there exists a fair amount of studies that focus on entrepreneurship education, but a lot of them suffer from substantial heterogeneity and methodological flaws (Glaub & Frese (2011); McKenzie & Woodruff (2013)). The dissertation combines the ideas of using selection procedures for entrepreneurs with the idea of teaching entrepreneurial skills.

1.1.1 Selection in Entrepreneurship

Using the search term “personnel selection”, Google Scholar lists more than 2.6 million results as of today. There is a vast amount of studies examining possible selection variables and instruments in a human resources context (e.g. Schmidt & Hunter, 1998; Judge, Higgins, Thoresen, & Barrick, 1999; Barrick & Mount, 1991; Hogan, 1991; Hunter & Hunter, 1984; Borman & Motowidlo, 1997; Thorndike, 1949; and lots of others), mostly focusing on the question of how to predict (un)desirable behavior. We extend the existing literature to the field of entrepreneurship that by now has only fragmentary used the ideas and methods of selection. With regard to the criticism of König, Klehe, Berchtold, & Kleinmann (2010), we do so in a practical surrounding to narrow the scientist-practitioner gap (the “gap between what scientists say and what practitioners do”, p. 17): we analyze personnel selection when predicting entrepreneurs’ loan defaults.

Naturally, the use of selection instruments brings along problems of faking. A lot of variables and procedures are prone to faking, i.e. an applicant is able to adapt his or her answers to appear (un)favorable. A lot of scientists have been researching the effects of faking on personnel selection (e.g. Birkeland, Manson, Kisamore, Brannick, & Smith (2006); Christiansen, Goffin, Johnston, & Rothstein (1994); Dilchert, Ones, Viswesvaran, & Deller (2006); Donovan, Dwight & Hurtz (2003); Dwight & Alliger (1997); Ellingson, Sackett, & Hough (1999); Griffith, Chmielowski, & Yoshita (2007); Hayes (2013); Ones, Viswesvaran, & Reiss (1996); Paulhus (1984); Rosse, Stecher, Miller, & Levin (1998); Van Iddekinge, Roth, Raymark, & Odle-Dusseau (2012); and again lots of others). We address this issue for using selection instruments when predicting entrepreneurs’ loan defaults regarding two aspects. First, we use an alternative approach to examining faking via curve distributions. Second, we analyze predictive validities with regard to low- and high-stakes situations.

Low-stakes situations are situations where there is nothing at stake for the participants, i.e. the selection instrument has no consequence whatsoever for them. Low-stakes situations are mostly used for validating measures: a certain population or sample runs through the selection instrument(s), and the results are correlated with different measures of interest (for example job performance, fluctuation, theft, etc.). Look at the meta-analysis by Barrick & Mount (1991) for several examples of using big five personality dimensions as predictors for job performance. However, the situation of interest for personnel selection is not a low-, but a high-stakes situation.

High-stakes situations are situations where the provided answers have a direct impact on the participant (e.g. when filling out a questionnaire as an applicant for a job, giving “wrong” or undesirable answers could result in not getting the job). Dilchert, Ones, Viswesvaran, & Deller (2006) state that “in fact, all high-stakes assessments are likely to elicit deception from assessees” (p.210). But there is still disagreement among scientists as well as practitioners to what extent faking actually happens in a high-stakes situation – and whether it has an effect on selection decisions (Dopnovan, Dwight, & Schneider, 2013; Ellingson, Sackett, & Hough, 1999; Griffith, Chmielowski, & Yoshita, 2007; Hayes, 2013; Ones, Viswesvaran, & Reiss, 1996; Rosse, Stecher, Miller, & Levin, 1998). The question whether predictors that work well in a low-stakes context can be used to predict high-stakes performance as well remains unanswered, but is of crucial importance for practitioners. This dissertation offers a first step to answering these questions: We show empirically that predictive models built with low-stakes data do not necessarily generalize to high-stakes situations, while models built with high-stakes data work well as predictor in the same high stakes setting. Using selection instruments for predicting entrepreneurs’ loan defaults, the study is highly practice-oriented. Extending this practical orientation, the second part of this dissertation focusses on how to educate entrepreneurs to be successful.

1.1.2 Training in Entrepreneurship

There is a fair amount of studies that focus on the development of entrepreneurial skills and how to teach entrepreneurs to be successful (Frese, Gielnik, & Mensmann, in press; Gielnik et al., 2014; Glaub, Frese, Fischer, Klemm, 2014; Bischoff, 2015; Stark, 2015; de Mel, McKenzie, & Woodruff, 2014; Martin, McNally, & Kay, 2013; Martinez et al., 2010; Oosterbeck, Praag, & Ijsselstein, 2010; Barr, Baker, & Markham, 2009; Rasmussen & Sørheim, 2006; Honig, 2004; Fiet, 2001b; Gorman, Hanlon, & King, 1997). Yet, as shown in Glaub & Frese's (2011) review, a large share of these studies suffer from flaws of methodological issues like the absence of a randomized control group or no pre-/post-test design. There are also few studies that test different treatment methods for their effectiveness in teaching entrepreneurs (McKenzie & Woodruff; 2013). We address this issue in presenting a randomized controlled trial study amongst business owners with two different treatments (action-based vs. knowledge-based) and additionally a non-treatment control group.

As a theoretical foundation for the treatment, we used the theory of personal initiative (PI). PI is positively correlated with entrepreneurial activity and success (Rauch & Frese, 2007; Krauss, 2003; Utsch & Rauch, 2000; Koop, De Reu & Frese, 2000). Glaub et al. (2014) have shown an increase in entrepreneurs success mediated by PI through an action-based training approach. Yet, the majority of entrepreneurship training programs to date consists of lectures and case studies (Rideout & Gray, 2013). We thus used the training developed by Glaub et al. (2014) as a foundation to develop two different treatments, one action-based and one knowledge-based. We analyze the effects of the treatments on the four levels proposed by Kirkpatrick (1959) for evaluating training programs: reaction, knowledge, behavior, and success.

1.2 The Conception of the Dissertation

With this dissertation, I present a human resources approach to entrepreneurship. In the second chapter, my co-authors and I empirically examine the usage of HR selection instruments for predicting small business owners' loan defaults. Furthermore, we add to the existing literature in using an alternative approach via curve distributions, and we show that predictive models for high-stakes situations should be based on high-stakes data instead of low-stakes data. We do so in presenting two studies researching small business owners applying for credits in developing countries.

The third chapter focuses on the development of entrepreneurial skills to help increasing entrepreneurial success. We compare two different treatments (action-based vs. knowledge-based) designed to teach personal initiative (PI) to small business owners with a randomized controlled trial study that was done in Uganda. Our results show that the knowledge-based training primarily increased PI knowledge, while the action-based training primarily increased PI behavior. Both treatments had a small but significant positive effect on the success of the firms while the control group decreased in success.

The fourth chapter concludes the dissertation with a general discussion of chapters two and three as well as suggestions for future research and practical implications.

CHAPTER 2

Predicting Loan Default of Small Business Borrowers using Personality Measures: Two Studies on Prediction Models in low- and high-stakes Settings in Developing Countries

2.1 Abstract

The study seeks to contribute to entrepreneurship research in the following ways: First, this is the first study that examines empirically how to predict small business owners' loan defaults. Second, we use an alternative approach to examining faking via curve distributions. Third, we show empirically that predictive models built with low-stakes data do not necessarily generalize to high stakes situations of credit applications with banks. Study 1 results show that prediction models of paying back credits are different in high and low-stakes situations (N=509). In a second study, the distributions of psychometrics relevant for entrepreneurs applying for a loan – Extraversion, Conscientiousness and Integrity – are different for applicants when in low- versus high-stakes settings. While in a low-stakes setting the curve is not skewed and resembles a Gaussian normal distribution (based on an N=1,715), in a high-stakes setting the curves are highly negatively skewed and resemble a Mirrored Gumbel distribution (based on N=37,489). One practical implication is that the validity of models developed in low-stakes situations cannot be easily transferred to a high stakes situations; unfortunately, this implies that many popular selection instruments developed by using volunteers in low-stakes research settings are not generalizable to a real-life “selection” situation. However, models developed on data collected in high stakes situations can predict loan default well in the same high stakes setting.

2.2 Theory

Micro and small business lending has revolutionized access to finance in developing countries ever since Yunus (1999) has introduced “banking for the poor”. Some experimental evidence showed small-scale business owners to use credit well producing important increments in wealth and effectiveness of the firms’ owners. However, there is also the possibility of misuse of credit if it is easily available. Indeed, original studies and reviews generally suggest that there are heterogeneous effects of micro-credits on firm success – both positive as well as not so positive effects (de Mel, Mckenzie, & Woodruff, 2014; de Mel, McKenzie, & Woodruff, 2008; Goldberg, 2005; Karlan & Zimman, 2009). Micro-credits can also be used to buy alcohol and have a good time for a few days or a month. Yunus (1999) essentially argues that misuse is seldom and can be checked by collective control. However, establishing collective control by credit groups increases costs and has not worked effectively for relatively larger loan sizes required by some businesses in developing countries. Both institutions and borrowers tend towards individual-liability loans rather than group loans, making it of even greater importance to develop new methods to evaluate credit risk.

Our study contributes to issues around selecting the right people for micro and small business lending and the possibility to predict loan defaults. In contrast to the developed world, banks in developing countries cannot rely on traditional approaches to reduce misuse of credits. In the developed world, banks reduce the misuse of credits by relying on collateral as security and by relying on credit history of an individual as a predictor of reliable loan repayment. With business owners, most banks demand to see a clear and transparent business plan for a business. However, there are a number of prerequisites for using collateral, credit history, and estimates of viability of business plans: First, people for credit must be able to provide collateral – this is not the case for most small and micro-business owners in developing countries; often there is no such thing as a property register that can be used by

banks. Second, credit history requires prior credits provided – however, bankers for the poor cannot rely on this instrument because by its very nature, many micro-business owners are unbanked – they have never used credits before. Moreover, institutions that provide data on credit history do not exist in many developing countries. Third, estimates of the viability of a business plan requires specialists who are able to understand those business plans and who are able to predict whether a business plan will work out in the future. Even very experienced business investors are not very good in predicting the future success of a business based on business plans with the very best of information (Rosenbusch, Brinckmann, & Mueller, 2013). Micro-business owners are also unlikely to write effective business plans and most banks do not have specialists for providing good diagnostics of business plans. Fourth, all these established procedures used by banks in the developed world – establishing collaterals, getting credit history, and establishing the viability of business plans – are costly. Since micro- and small-business loans are by its very nature small and the extra costs can never be recovered from interest payments, the usual response by banks was not to serve the poor (Klinger, Khwaja, & Del Carpio, 2013).

This situation convinced Klinger, Khwaja, & Del Carpio (2013) to suggest an alternative strategy for banks to select the right people for a credit. Based on the psychological work in the area of predicting entrepreneurial success, they suggested that psychological variables can be used for prediction of success and honesty. There is a large and highly successful literature on the prediction of performance in the area of employee performance that suggests that intelligence (general mental ability), the personality trait of conscientiousness, and integrity are the best predictors of performance of employees (Hunter & Hunter, 1984). In addition, integrity testing has been used for employee selection (Hunter & Hunter, 1984; Ones et al., 1993; van Iddekinge, Roth, Raymark, & Odle-Dusseau, 2012).

There is good evidence that personality in general, and in particular achievement motive (which is part of the trait of conscientiousness) are good predictors of success in

entrepreneurs, as shown by a recent overview of meta-analyses in this area (Frese & Gielnik, 2014). Indeed, the validity of psychological personality factors, such as achievement motive for success has proven to be higher than any other factor thought to be important for success in small business people, such as social or human capital (Frese & Gielnik, 2014). Of course, entrepreneurial success is affected by multiple and highly varied predictors but any prediction model requires a certain degree of stability of predictors. Personality is relatively stable across time and is, therefore, useful for predicting entrepreneurial success. This in turn will affect pay back of credits by small business people. There is a large body of knowledge on personality variables of owners linked to success in running a business (Rauch & Frese, 2007). The psychological make-up of business owners goes back at least 80 years (Schumpeter, 1934) and was particularly well developed around the issue of achievement motive by McClelland (1967). Rauch & Frese (2007) conclude that “models of entrepreneurial success should include owners’ personality traits” (p. 27). Indeed, similar to Barrick & Mount (1991), the clearest relationships appear for personality traits related to conscientiousness, such as achievement motive and generalized self-efficacy (Rauch & Frese, 2007; similarly also Zhao, Seibert, & Lumpkin, 2010).

In addition, integrity (the tendency to be honest and to base one’s behavior on moral values) may also be an important factor in predicting loan default. Lenders typically focus not just on an applicants’ ability to repay, but also their willingness to repay. Unethical entrepreneurs may have no intention to pay back a credit and just take the extra cash to satisfy their immediate needs. This is particularly so in the context of developing countries, because it is easier to disappear in those countries and there is less recourse for banks to get back the loan (e.g. because no collateral has been put up for the loan). Thus, integrity tests may be useful in the entrepreneurship context as well. Therefore, it makes good sense to apply measures of personality and integrity for predicting the repayment of credit. This is a new area which has not been examined to our knowledge in the scientific literature (except by

Klinger et al., 2013); we contribute to this new area by examining one particular problem – the problem of faking.

The problem of faking has plagued the literature on employee selection. People are able to adapt their answers to appear more positive under conditions of high stakes testing. People can fake their answers on personality tests and possibly also on integrity tests, if they think it helps them to get positive results, e.g., getting a job or a credit.¹ To what extent does response distortion affect micro-entrepreneurs' answers? And how does this affect the predictive validity and usability of personality and integrity tests to ascertain potential non-payers of credits among the applicants for a credit in developing countries?

One approach to detect faking has been to use scales to measure response biases, lying, or social or impression management scales (McGrath, Mitchell, Kim, & Hough, 2010). Many personality inventories include such scales. Unfortunately, there is evidence that although differences in these scales exist these scales do not help to improve validities (Hough, Eaton, Dunnette, Kamp, & McCloy, 1990): First, there is evidence that impression management scales are susceptible to faking themselves (Dwight & Alliger, 1997; Kroger & Turnbull, 1975). Second, Ziegler et al. (2011) summarize that the ability of impression management scales to detect faking is questionable, mostly because of overlapping trait variance of these scales with personality. Third, Rosse, Stecher, Miller, & Levin (1998) explain several methodological issues when relying on impression management scales in selection contexts. The authors provide evidence that response distortion can have a significant effect on who is hired, and that there are differences in response distortion between high stakes (job applicants) and low-stakes situations.

Most research in this area found that people are able to and do change their answers on personality or integrity test when instructed to do so and when certain answers produce

¹ The only tests that are immune to response distortions are knowledge and ability tests, such as a test of general mental ability, because one cannot fake a true answer in a performance test.

rewards. But there is disagreement whether response distorting just leads to higher means in all participants. For example, if people with high and low integrity all control their impulses to answer the test truthfully and just add an increment of additional unsubstantiated integrity to the test, then this does not affect the validity of a test. In this case the rank order of test results are similar across high or low-stakes situations (Ellingson, Sacket, & Hough, 1998; Ones, Viswesvaran, & Reiss, 1996; Hogan, Hogan, & Roberts, 1996; Christiansen, Goffin, Johnston, & Rothstein, 1994). However, Alliger & Dwight (2000) as well as Donovan, Dwight, & Hurtz (2003) criticized the reliance on equal criterion-related validity in low and high stakes situation, as selection decisions may be altered; when “good” candidates are taken, this may result in a higher percentage of false positives (hiring the “wrong” applicant or giving the “wrong” person a credit). Dilchert, Ones, Viswesvaran, & Deller (2006) state that “in fact, all high-stakes assessments are likely to elicit deception from assesseees” (p.210).

In this article we examine the effects of high-stakes settings on response distortion in terms of distributions of answer across the spectrum of possible answers. It is surprising that there are so few real life studies that compared such distributions across high and low stake situations. Yet, this should provide an answer to the question on whether response distortion in high stakes situations occur (e.g., in personality and integrity tests). Moreover, these studies need to be done in real life situations and not just in simulations. Many studies have put people into imaginary situations, such as applying for a job (or applying for a credit); their answers were then compared to answers from the same group of people who were not instructed to imagine a situation in which they needed to make a good impression. The problem with such studies is that simulating any situation is really by definition a low-stakes situation, precisely because the participants in such studies only simulate the real thing (e.g., an application).

On a more general level, the setting of small business people applying for credit allows new possibilities to examine validity of the use of personality tests in a high stakes

situation using a clear simple and highly objective dependent variable – repayment or default on a loan. In doing this, we follow Stark, Chernyshenko, Chan, Lee, & Drasgow's (2001) call for research on the differences between low and high-stakes settings using larger samples.

We present two studies on whether people give different answers in a high-stakes context compared to a low-stakes situation. We contribute to faking research by analyzing the differences between low and high-stakes situations in examining variable distributions. We attempt to make three contributions: 1. We show that response distortion exists in small business owners applying for a credit. 2. We do this by examining distribution data as a new methodology for detecting differences between low and high-stakes settings. 3. We show the predictive performance of personality measures on default in low- compared to high-stakes situations. The first study that was done in Kenya contains both low-stakes and high-stakes data – here we analyze the prevalence of response distortion in a high-stakes setting with a sample of entrepreneurs applying for a loan. We also analyzed how two different predictive models (based on low- and high-stakes data, respectively) perform in predicting the important criterion of paying back the loan (N = 8,028). Study 2 extended our sample to other countries, some with low-stakes data and some with high-stakes data, and we examined at the distribution changes between low and high-stakes as an alternative methodology (N = 37,489, including the sample of Study 1). We found that there were high differences in personality variables and an integrity test distributions between high and low-stakes.

2.2.1 Faking and Response Distortion

Some researchers claim that only a small percentage of participants' answers in high-stakes situations suffer from response distortion (Levashina, Morgeson, & Campion, 2009), leaving criterion-related validities relatively stable. In contrast, Donovan et al. (2003) found a high degree of prevalence of faking using the randomized response technique (a technique where – simply spoken – people can anonymously give true answers to delicate or socially

disputable questions); their data suggested that around one third of the study participants admitted to having engaged in some kind of faking in their last application. Griffith, Chmielowski, & Yoshita (2007) as well as Ziegler et al. (2011) come to a comparable conclusion. Even these data may be underestimates because faking admitted via retrospective self-reports – as used in the study by Donovan et al. (2003) – might lead to memory distortions and socially desirable answers that would reduce the incidence of faking.

Do people give different answers to personality measures in high-stakes settings compared to low-stakes settings? Paulhus (1984) distinguished two components of response distortion: impression management (faking) and self-deception. While impression management involves an active process where applicants decide to knowingly distort their self-presentation and give false or exaggerated answers, self-deception happens without conscious intention to deceive and applicants are convinced that the answers given are true. Usually, faking research focuses on impression management. Yet, Ones et al. (1996) found substantial correlations between both factors of the two-component model. While faking usually refers to the process of consciously giving an answer that is not (completely) true, response distortion additionally covers non-conscious processes leading to higher scores in a high-stakes situation than in a low-stakes assessment (Ziegler et al., 2011).

Differences in answers to personality tests between high and low-stakes situations may be a function of intentional faking – here people exaggerate or even give false information to get their wishes fulfilled (e.g., getting a credit that can be used for all sorts of wishes). However, the response distortion concept might be broader and also includes non-intentional distortions. There may also be distortions in low-stake situations. First, anecdotal evidence suggests that people in a low-stakes situation put in little effort in answering questions, because there are no good reasons to be careful; thus, they often read the questions only superficially. In contrast, people in a high-stakes situation read the questions with high attentiveness and caution to understand them correctly. Thus, conceivably high-stakes

responses may be the results of more careful thoughts in contrast to low-stakes responses which might be superficial. Second, priming effects may be operative as well – a high-stakes situation typically primes achievement themes (achievement at work) and, thus, it primes achievement motives and increases the tendency to answer questions corresponding to the primed high achievement themes (Shantz, & Latham, 2011; Stajkovic, Locke, & Blair 2006). Third, a self-serving positivity bias may be at work – although this bias may be differentially distributed in different cultures and it may be reduced in depressed individuals (Mezulis, Abramson, Hyde, & Hankin, 2004).

The above discussion shows that we do not need to assume that low-stakes data are necessarily ‘true’ scores and high-stakes data are assumed to be more easily faked; rather it is possible that differences between high- and low-stakes answers are due to intentional faking, but also to non-intentional response distortion. This leads us to change the perspective from a personality construct of response distortion to a situational approach (high- versus low-stakes settings) that may prime response distortions to some extent. However, even then potential differences between high- and low-stakes settings have important practical implications: Prediction models used for selection for banks that were developed in low-stakes settings (e.g., in scientific studies) may not show the same predictive power in high stake settings.

2.2.2 The Entrepreneurial Setting

To our knowledge, the present studies are the first ones to empirically examine response distortion in entrepreneurs from developing countries applying for a small bank loan. We believe that this is a very interesting population because small scale entrepreneurs in developing countries are often not highly educated, and they certainly are not used to taking personality or integrity tests; this would actually reduce the differences between high and low-stakes situations in this population. This population also allows to measure the outcome in an objective way: For banks, the most important variable is whether they are paid back their

loans (Klinger et al., 2013). Klinger et al. (2013) pointed out that the approach of using the owner's credit history is only possible in developed countries where detailed personal credit records are available. They developed the idea of using psychometric variables of the owner (personality, intelligence and integrity) of credit applicants to predict default via automated scoring.

Klinger et al. (2013) employed the personality dimensions of conscientiousness and extraversion, intelligence and integrity for an automated scoring approach amongst entrepreneurs applying for a loan in countries where there are no detailed personal credit records available. We employ this setting to analyze the prevalence of response distortion in a real-life high-stakes setting (= the loan application) compared to a low-stakes setting.

The differences between low and high-stakes settings in employees has been analyzed by Birkeland et al. (2006) in a meta-analysis where the authors found that applicants give different answers on scales that they view as particularly job-relevant in high-stakes contexts as compared to low-stakes contexts. Thus, entrepreneurs applying for a loan (high-stakes context) will provide different answers than entrepreneurs in a low-stakes setting on scales that they perceive as relevant for entrepreneurship and creditworthiness. Conscientiousness, extraversion and integrity tests seem relevant for paying back a loan, even for laypeople. This would then speak for stronger effects in these variables. In contrast, the effects should be smaller for emotional stability and for openness to experience because these two variables are not as clearly related to paying back a loan than conscientiousness, extraversion, and integrity. Thus, we hypothesize

H1: Entrepreneurs give different answers for the dimensions Extraversion, Conscientiousness, and Integrity in a high-stakes setting (applying for a loan) compared to a low-stakes setting (this may also apply to a lesser extent to Emotional stability and Openness to Experience).

We additionally hypothesize that a different prediction model developed for a low-stakes context does not generalize to one developed for a high-stakes context. This leads to our hypothesis H2:

H2: Prediction models only predict loan defaults in the context in which they were developed and assessed. If a prediction model is based on low-stakes data, it performs well in a low-stakes context but it does not predict credit default in a high-stakes context and vice versa.

2.3 Study 1

Potential differences of high and low-stakes situations are of obvious major practical importance because the majority of prediction instruments used for selection are developed and validated in low-stakes research settings. When entrepreneurs, who are not currently applying for a credit, are recruited as volunteers, the resulting correlations between their measured personality traits and entrepreneurial success or paying back a credit may not generalize to entrepreneurs, who apply for a credit. Thus, what appears to be a highly valid test in a low-stakes situation (volunteers) may not be valid in a high stakes situation (attempting to get a credit).

2.3.1 Method

2.3.2 Design

We collected data under two different conditions in Kenya. For the low-stakes situation, we approached existing clients of banks through the banks to take our computer-based test. The business owners had already received their loans at least six months prior to

this data assessment – this was a low-stakes setting. Moreover, they were explicitly told that their responses would not be shared with the banks and were for research purposes only.

Regarding the high-stakes situation, we partnered with banks that included the questionnaire as a mandatory part of the process to apply for a loan. In this case, the score on the test was used to make the approval or rejection decision on the loan application, and the clients knew this to be the case. The same questionnaire was used in both cases.

2.3.2.1 Sample

We used a sample of micro entrepreneurs of $N = 8,028$, of which 421 were in the low-stakes setting, whereas the majority ($N = 7,607$) of our participants were in the high-stakes setting. The sample consists of small and medium sized business owners from Kenya – this clientele is not used to filling out personality surveys frequently. This sample may also show only a low level of education Table 2.1 shows the characteristics of the sample. The age of the participants ranged from under 25 to over 64, and 58% of our participants were men. Most of the business owners in both settings had been running their firm for more than three years, and in the low-stakes setting, around half of the entrepreneurs had 1-5 employees. There were differences between low- and high-stakes situations for the business sectors commerce ($t(7,869) = -18.17, p < .001$) and production ($t(7,869) = 4.58, p < .001$) as well as for business revenues ($t(8,024) = -13.89, p < .001$). The low-stakes data were collected from banks that gave smaller microfinance-sized loans, while the high-stakes data were from banks that provided larger loans; the high-stakes banks also had a product for traders (i.e. commerce) whereas the low-stakes banks were strictly microfinance loan institutions. This is also reflected in the size of the loans. We, therefore, controlled for business revenues and sector in the further analyses.

2.3.2.2 Measures

Data collection² was done with a computer-based test; for Study 1, the languages of the questionnaire were English and Swahili in Kenya. In addition, Study 2 included Spanish as well as Afrikaans forms of the tests.

*Personality.*³ We used a commercially available test for assessing personality dimensions. Due to time constraints, this battery only included 4 of the ‘big 5’ dimensions; it contained more items of conscientiousness than of the other facets; previous research suggests that conscientiousness is highly relevant for entrepreneurial outcomes (Rauch & Frese, 2007; Zhao et al., 2010). The test consists of 86 items with answer keys of “yes” or “no”. Negatively poled items were recoded. The personality scores were calculated using the test provider’s algorithm.

*Integrity.*³ To assess integrity, we used a commercially available integrity-test that is a derivative of the Reid report and PSI (Ash, 1970; Ash, 1971; London House Press, 1980). The test consists of 78 items that have to be answered on different scales (e.g. a 5-point Likert scale ranging from “definitely no” to “definitely yes”, a 5-point Likert scale ranging from “never” to “very often”, or a percentage estimate on a 6-point Likert scale from “Nearly 100%” to “Nearly 0%”), inquiring attitudes regarding theft and dishonest behavior. The score was calculating using the test provider’s algorithm.

2.3.2.3 Calculations

For our calculations, we used IBM SPSS Statistics V21.

² EFL Global Ltd. provided us with the data; the exact use of items, constructs, and weighting of constructs to predict pay back and thus to select credit for business owners cannot be disclosed (partly also because of the contracts between EFL Global and the providers of scales). Thus, both the description of the scales, as well as the models discussed for testing of H3, can be described only in generic terms.

³ Due to copyright issues, we are not able to reproduce sample items for these scales.

Table 2.1

Distribution of Participants in Kenya (Study 1).

	Low-stakes	High-stakes
N	421	7,607
Gender = Male	252 (59.9%)	4,401 (57.9%)
Commerce Sector Dummy	259 (61.5%)	6705 (88.1%)
Production Sector Dummy	35 (8.3%)	283 (3.7%)
Agricultural Sector Dummy	8 (1.9%)	149 (2.0%)
Age		
Under 25	50 (3.1%)	710 (4.5%)
25-34	408 (25.1%)	4,644 (29.6%)
35-44	591 (36.4%)	6,160 (39.3%)
45-54	358 (22.0%)	3,182 (20.3%)
55-64	166 (10.2%)	855 (5.5%)
Over 64	43 (2.6%)	122 (0.8%)
Business Revenues		
Less than \$1k	141 (33.5%)	785 (10.3%)
\$1k - \$10k	228 (54.2%)	4,273 (56.2%)
\$10k - \$100k	48 (11.4%)	2,453 (32.2%)
\$100k - \$1m	3 (0.7%)	85 (1.1%)
\$1m - \$10m	0 (0.0%)	10 (0.1%)

2.3.3 Results

Table 2.2 presents the intercorrelations of the variables used in the study. Hypothesis H1 states that different answers appear for the dimensions extraversion, conscientiousness,

Chapter 2 – Predicting Loan Default of Small Business Borrowers

Table 2.2

Intercorrelations of Study 1 Variables.

Variables and Scales	N	M	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Stakes (0 = low-stakes, 1 = high-stakes)	8,028	.95	.22										
2. Gender (1 = male, 2 = female)	8,028	1.42	.49	.01									
3. Business Revenues	8,026	2.22	.66	.15***	-.04**								
4. Emotional Stability	8,028	5.59	1.88	.22***	-.01	.06***							
5. Extraversion	8,028	25.77	3.39	.27***	.00	.16***	.51***						
6. Conscientiousness	8,028	24.28	3.56	.32***	-.01	.07***	.55***	.60***					
7. Openness to Experience	8,028	6.74	1.19	.10***	.03*	.05***	-.05***	.27***	.21***				
8. Integrity	7,984	81.66	20.36	.41***	.01	.13***	.51***	.54***	.63***	.16***			
9. Commerce Sector Dummy (1= yes, 0 = no)	7,871	.88	.32	.20***	.04**	.10***	.06***	.12***	.13***	.10***	.14***		
10. Production Sector Dummy (1= yes, 0 = no)	7,871	.04	.20	-.05***	-.02	-.07***	-.03**	-.10***	-.06***	-.06***	-.07***	-.57***	
11. Aggricultural Sector Dummy (1= yes, 0 = no)	7,871	.02	.14	.00	.01	-.04***	-.03**	-.03*	-.04**	-.02*	-.03**	-.40***	-.03**

Note. * correlation is significant at the .05 level (2-tailed). ** correlation is significant at the .01 level (2-tailed). *** correlation is significant at the .001 level (2-tailed).

and integrity in the high-stakes setting (applying for a loan) compared to a low-stakes setting (unrelated to getting a loan). Table 2.3 presents the means and standard deviations of the variables for both the low- and the high-stakes setting. Additionally, we conducted a One-Way ANCOVA to determine a statistically significant difference between low- and high-stakes settings on personality variables (extraversion, conscientiousness, emotional stability, openness to experience and integrity) controlling for gender, business sector and business revenues. Results showed a significant effect of stakes on emotional stability ($F(1, 7865) = 388.97, p < .001, \eta^2 = .05$), extraversion ($F(1, 7863) = 525.49, p < .001, \eta^2 = .06$), conscientiousness ($F(1, 7863) = 771.27, p < .001, \eta^2 = .09$), openness to experience ($F(1, 7863) = 48.49, p < .001, \eta^2 = .01$) and integrity ($F(1, 7819) = 1381.96, p < .001, \eta^2 = .15$). Effect size of the differences were small for openness to experience, emotional stability and for extraversion, but much higher for conscientiousness and for Integrity. The differences are in line with our hypothesis H1 with more positive scores in the high-stakes condition.

Table 2.3

Mean Differences in Personality Variables between High and Low-stakes Settings (Study 1).

	Low-stakes Setting			High-stakes Setting		
	N	M	SD	N	M	SD
Emotional Stability	421	3.85	1.99	7,607	5.69	1.83
Extraversion	421	21.88	4.31	7,607	25.98	3.20
Conscientiousness	421	19.51	3.73	7,607	24.55	3.36
Openness to Experience	421	6.24	1.31	7,607	6.76	1.18
Integrity	386	45.10	23.96	7,598	83.51	18.30

Hypothesis H2 states that prediction models only work well in the context in which the model was built and assessed. In order to test this hypothesis and to analyze the rank ordering ability of models built on low-stakes data to high-stakes applications, and vice versa, we organized the sample in the following way.

First of all, it is important to have equal sample sizes as metrics of rank ordering power are affected by sample size (Deltas, 2003). We randomly selected a subset of observations from the high-stakes data in Kenya to create a dataset with the same number of observations (342) and same number of defaults (i.e. failing to pay back the loan) (167) as in a low-stakes setting in Kenya. Second, to assess how well a model works, it has to be assessed out of sample (i.e. not with data used to make the model) to avoid a biased model / prediction. Therefore, with each the high- and the low-stakes sample, a random 80% of observations were selected and we ran a simple standard algorithm to build a credit scoring probability of default model (backwards stepwise logit regression). That model was then applied to the remaining 20% hold-out data to assess its ability to predict default out of sample within the same situation (low-stakes or high-stakes). For comparison, the low-stakes model then was applied to the high-stakes data hold-out sample, and the high-stakes model was applied to the low-stakes hold out sample for directly equivalent comparisons.

The predictive power is measured by a gini coefficient, a standard metric of model power in credit scoring (Thomas, Edelman, & Crook, 2002; Mays, 2004; Anderson, 2007). The results can be seen in Table 2.4. As can be seen, the model built on low-stakes data works well on low-stakes applicants but has almost no predictive power for high-stakes applicants. Vice versa, the model built on high-stakes data does not work well in a low-stakes context, but performs well for high-stakes applicants. The findings support H2.

Table 2.4

How well do Models from the Low-stakes Situation translate to the High-stakes Situation and vice versa? (Study 1).

	Achieves this Gini Coefficient on Low- Stakes Borrowers	Achieves this Gini Coefficient on High- Stakes Borrowers
Model built on Low-Stakes data	35.0%	1.8%
Model built on High-Stakes Data	5.9%	20.9%

2.3.4 Discussion

Hypothesis H1 implies that the means of personality and integrity variables differ between low- and high-stakes settings; the results support this Hypothesis. An additional ANCOVA controlling for business sector and business revenues showed medium to large effects of stakes on the variables emotional stability ($F(1, 7864) = 388.98, p < .001$), extraversion ($F(1, 7864) = 525.58, p < .001$), conscientiousness ($F(1, 7864) = 771.18, p < .001$); openness to experience ($F(1, 7864) = 48.53, p < .001$) and integrity ($F(1, 7820) = 1382.11, p < .001$). We thus conclude that entrepreneurs give different answers for the dimensions extraversion, conscientiousness, emotional stability, openness to experience, and integrity in a high-stakes setting compared to a low-stakes setting.

To test Hypothesis 2 (a prediction model predicts loan default only in the context it has been developed in). We applied a credit scoring model based on either low- or high-stakes data to check how well the model is able to predict payment default among existing low- or high-stakes applicants. The results support our hypothesis: a model that is based on low-

stakes data is able to predict payment default among low-stakes test-takers with a gini coefficient of 35.0% (but only 1.8% for high-stakes applicants). Vice-versa, a model built on high-stakes data is able to predict performance among high-stakes applicants with a gini coefficient of 20.9% (but only 5.9% for low-stakes applicants). Our findings suggest that personality or integrity scales are able to predict performance in a high-stakes setting only if the prediction model is also based on data assessed in a high-stakes context.

2.4 Study 2

Study 2 is based on much larger samples from various developing countries than Study 1 and we show distributions across high- and low-stakes situations. By focusing on distributions we test the hypothesis that there is just a general shift of all scores to better impressions in a high-stakes situation (as compared to low-stakes); according to this hypothesis there would be a similar rank ordering from high- to low-stakes situations. We suggest an alternative hypothesis: The distributions change radically from high- to low-stakes situations. Thus, we argue that differences in distributions imply considerable changes in rank ordering. A simple example may explain this: Assume a variable is distributed normally around the values from 1 to 5, and 45 people take the test. Table 2.5 shows how the 45 people would be distributed. A person scoring on 5 would belong to the top 11% of all test takers. However, if the distribution is extremely left-skewed (where percentages steadily grow from 1 to 5), the majority of people (33,3%) would have the highest score. It is unlikely that an extreme distribution of this form shows the same rank order as a normal distribution.

Table 2.5

Relative Positions in Different Distributions (theoretical example).

Score	1	2	3	4	5
N (normal distribution)	5	10	15	10	5
% of total N	0.11	0.22	0.33	0.22	0.11
N (right-skewed distribution)	3	6	9	12	15
% of total N	0.06	0.13	0.20	0.27	0.33

In the financial sector, a theory that is often used to assess risks is the extreme value theory (Gilli, 2006). While a normal distribution is useful when looking at the broad middle and the majority of observations, extreme value theory focuses on the tails (extreme ends) of the distributions. The tails of a distribution are of special interest in a credit selection context, where the focus is typically to identify the best (or worst) performers at the upper or lower end of the distribution, rather than to analyze the broad middle. One of the pioneers of extreme value distributions, Emil J. Gumbel, developed the (mirrored) Gumbel distribution as shown in figure 2.1 (Gumbel & Lieblein, 1954). Therefore we propose the following hypothesis:

H3: Personality variables (extraversion, conscientiousness, emotional stability, openness to experience and integrity) assessed in a high-stakes context follow a mirrored Gumbel distribution, whereas the variables assessed in a low-stakes context follow a normal distribution.

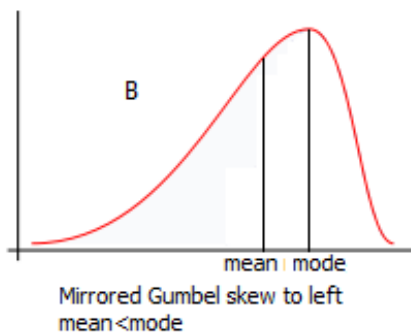


Figure 2.1. Mirrored Gumbel Distribution.

2.4.1 Method

2.4.1.1 Design

We employed the same study design as in Study 1, with the exception that we collected data not only in Kenya, but in 16 developing countries. For the low-stakes situation, we approached existing clients of banks in eight countries through the banks to take our computer-based test. Regarding the high-stakes situation, we partnered with banks operating across 16 countries that included the questionnaire to be filled out when applying for a loan.

2.4.1.2 Sample

We had an overall sample of 37,489 micro entrepreneurs of ; of these 1,715 provided measures in the low-stakes setting, whereas the majority ($n = 35,774$) of our participants filled out the questionnaire on the computer in a high-stakes setting (when applying for a credit). The response rate in the low-stakes setting was between 45% and 80%, depending on the institution. In the high-stakes setting, the test was obligatory. The age of the participants ranged from under 25 to over 64, and 67.8% of our participants were men. Most of the business owners in both settings had been running their firm for more than three years, and in

the low-stakes setting, around half of the entrepreneurs had 1-5 employees. Table 2.6 shows the characteristics of the sample.

2.4.1.3 Measures

Data collection consisted of a computer-based test, and it was done in English and Spanish as well as in Afrikaans and Swahili. The majority of the participants (94%) were assessed in English. Other than that, we used the same measures as in study 1 for personality and Integrity.

2.4.1.4 Calculations

For our calculations, we used IBM SPSS Statistics V21 and @RISK6.

Table 2.6

Distribution of Participants (Study 2).

	Low-stakes	High-stakes
N	1,715	35,774
Gender = Male	859 (50.1%)	23,409 (65.4%)
Commerce Sector Dummy	910 (53.1%)	24,730 (69.1%)
Production Sector Dummy	223 (13.0%)	2,542 (7.1%)
Agricultural Sector Dummy	44 (2.6%)	862 (2.4%)
Age		
Under 25	54 (3.1%)	1,735 (4.8%)
25-34	426 (24.8%)	10,780 (30.1%)
35-44	625 (36.4%)	13,575 (37.9%)
45-54	377 (22.0%)	7,315 (20.4%)
55-64	181 (10.6%)	2,063 (5.8%)
Over 64	44 (2.6%)	306 (0.9%)
Business Revenues		
Less than \$1k	854 (49.8%)	3,375 (9.4 %)
\$1k - \$10k	596 (34.8%)	17,682 (49.4 %)
\$10k - \$100k	195 (11.4%)	13,462 (37.6%)
\$100k - \$1m	36 (2.1%)	1,011 (2.8%)
\$1m - \$10m	4 (0.2%)	85 (0.2%)

2.4.2 Results

Hypothesis H3 states that personality variables (Extraversion, Conscientiousness, Emotional stability, Openness to Experience and integrity) assessed in a high-stakes context follow a mirrored Gumbel distribution, whereas the variables assessed in a low-stakes context follow a normal distribution. To find evidence for this hypothesis, we decided to first look at the frequency distribution graphs (figures 2.2 to 2.6). One can see that for the high-stakes groups the study variables have a right-skewed distribution, while there are no obvious deviations from normality in the low-stakes group.

To further analyze the data and to find evidence for our hypothesis, we looked at skewness and kurtosis of the distributions (Table 2.7). Bulmer (1979) suggests that a skewness between 0 and .5 equals a fairly symmetrical distribution, between .5 and 1.0 a distribution that is moderately skewed, and > 1.0 as highly skewed. While in the low-stakes setting, extraversion, conscientiousness, and integrity all were distributed fairly symmetrical, all of the high-stakes distributions for these variables were moderately to highly skewed. Emotional stability was distributed fairly symmetrical in both low- and high-stakes, yet the skewness variable was positive for the low-stakes setting and negative for the high-stakes setting. Openness to Experience was (moderately) skewed positively in the low-stakes setting and (moderately) skewed negatively in the high-stakes setting.

Cramer (1998) suggests to look at the test statistic $Z_{gl} = G1 / SE$ to analyze the probability of skewness due to sample drawing. He suggests that at $Z_{gl} < -2$ the population is very likely skewed negatively (at roughly .05 significance level). Z_{gl} was way smaller than -2 for all Extraversion ($Z_{gl} = -104.62$), Conscientiousness ($Z_{gl} = -50.15$), Emotional stability ($Z_{gl} = -19.15$), Openness to Experience ($Z_{gl} = -48.38$) and Integrity ($Z_{gl} = -44.08$) in the

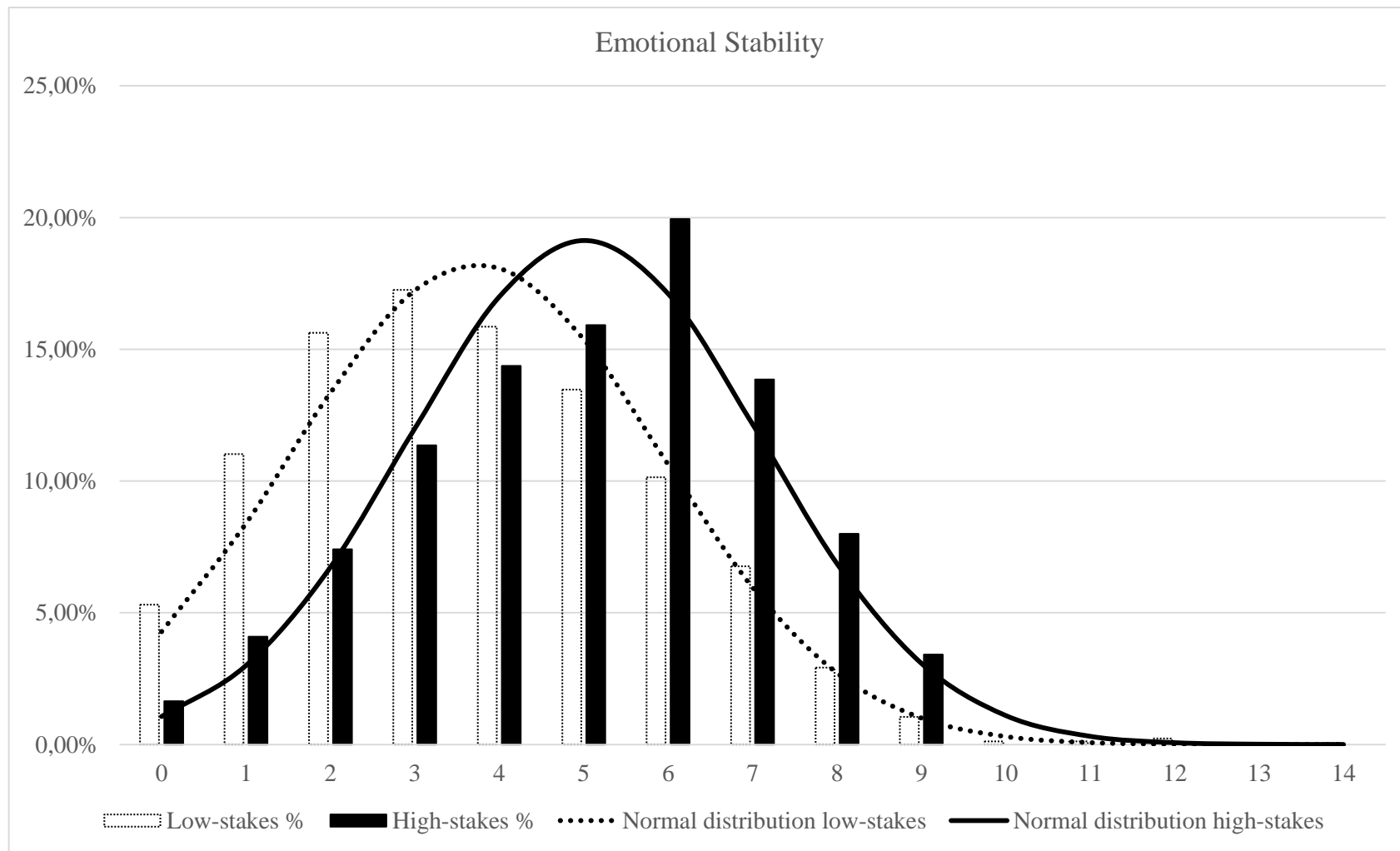


Figure 2.2. Distribution of Emotional Stability (Study 2).

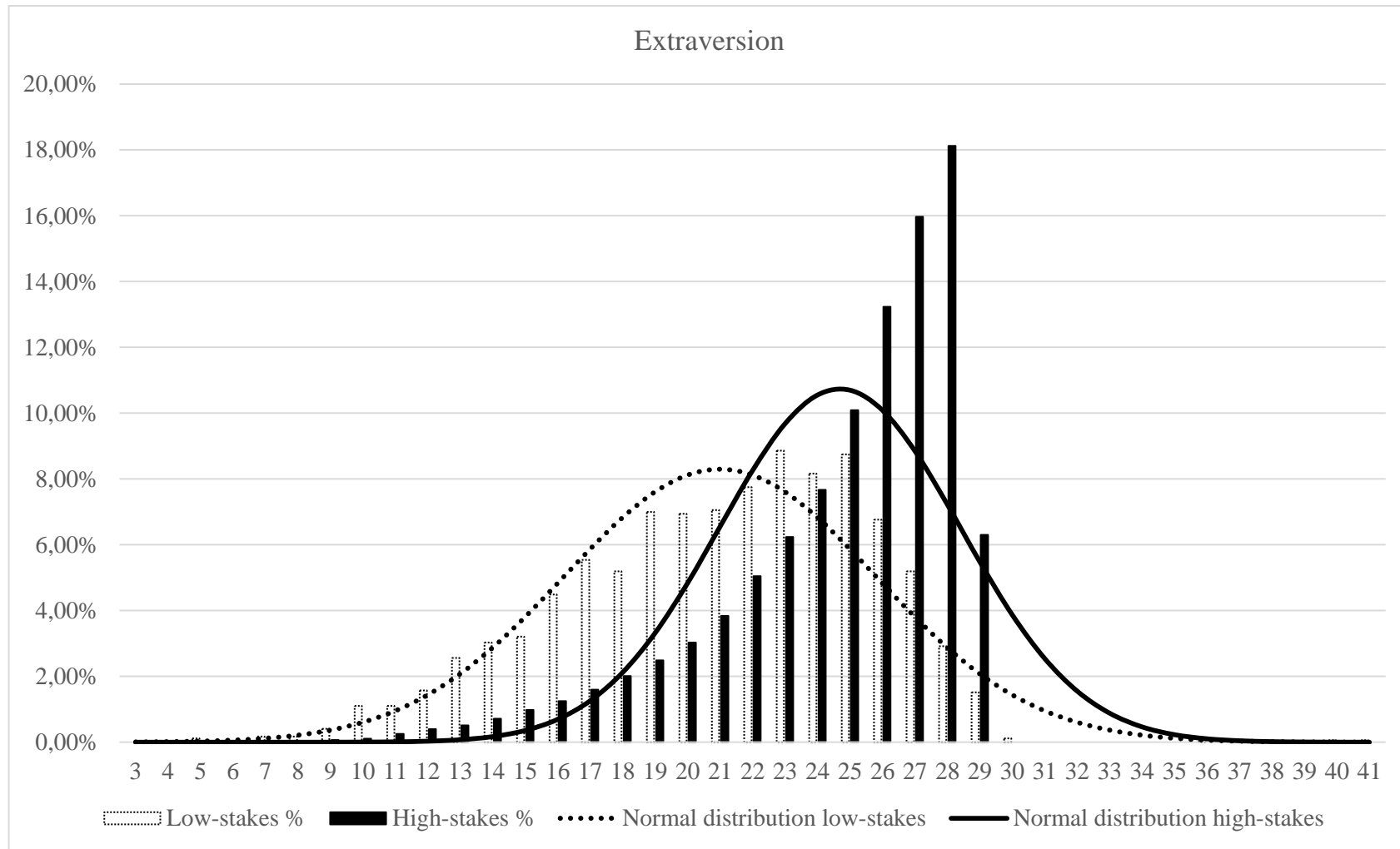


Figure 2.3. Distribution of Extraversion (Study 2).

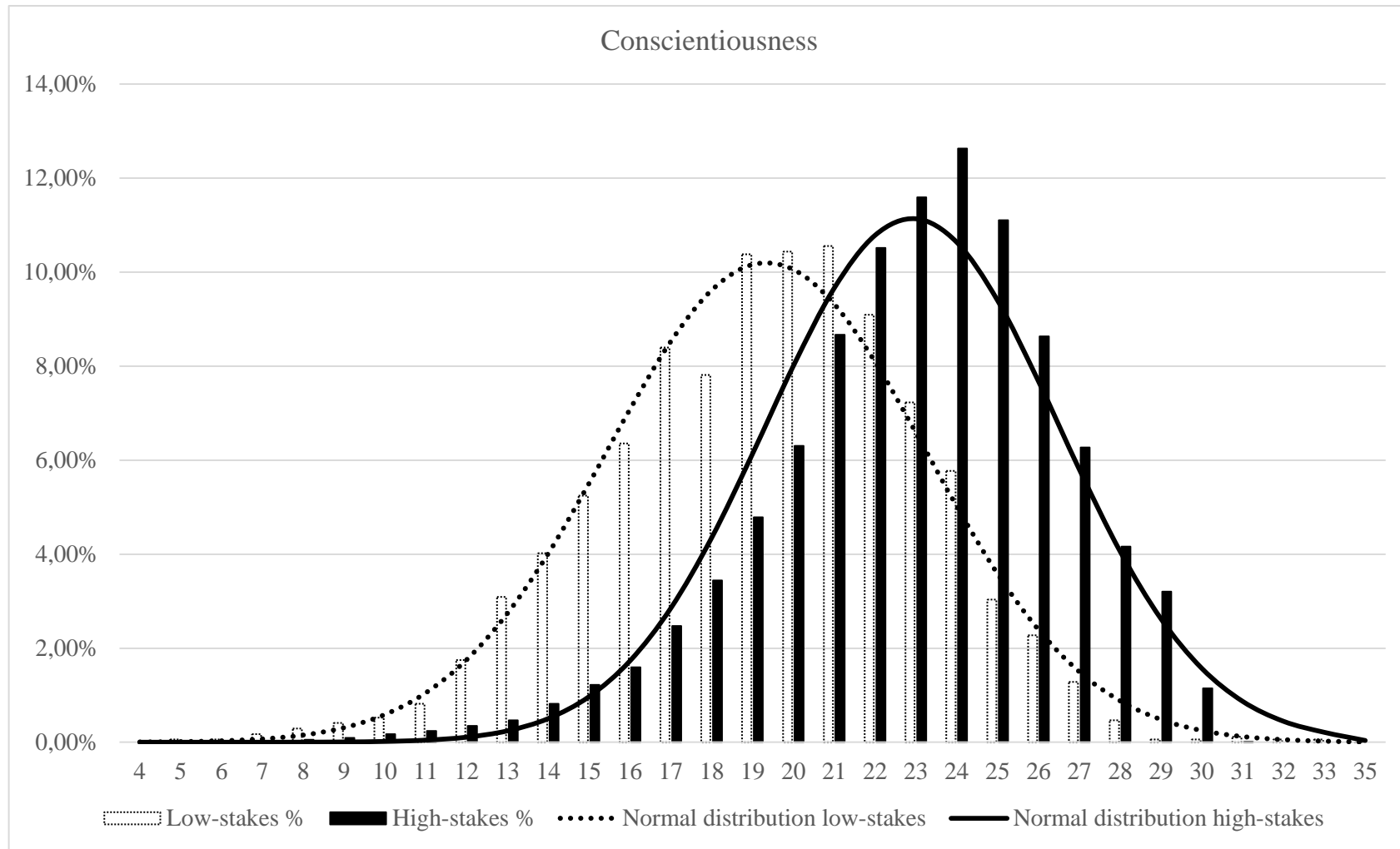


Figure 2.4. Distribution of Conscientiousness (Study 2).

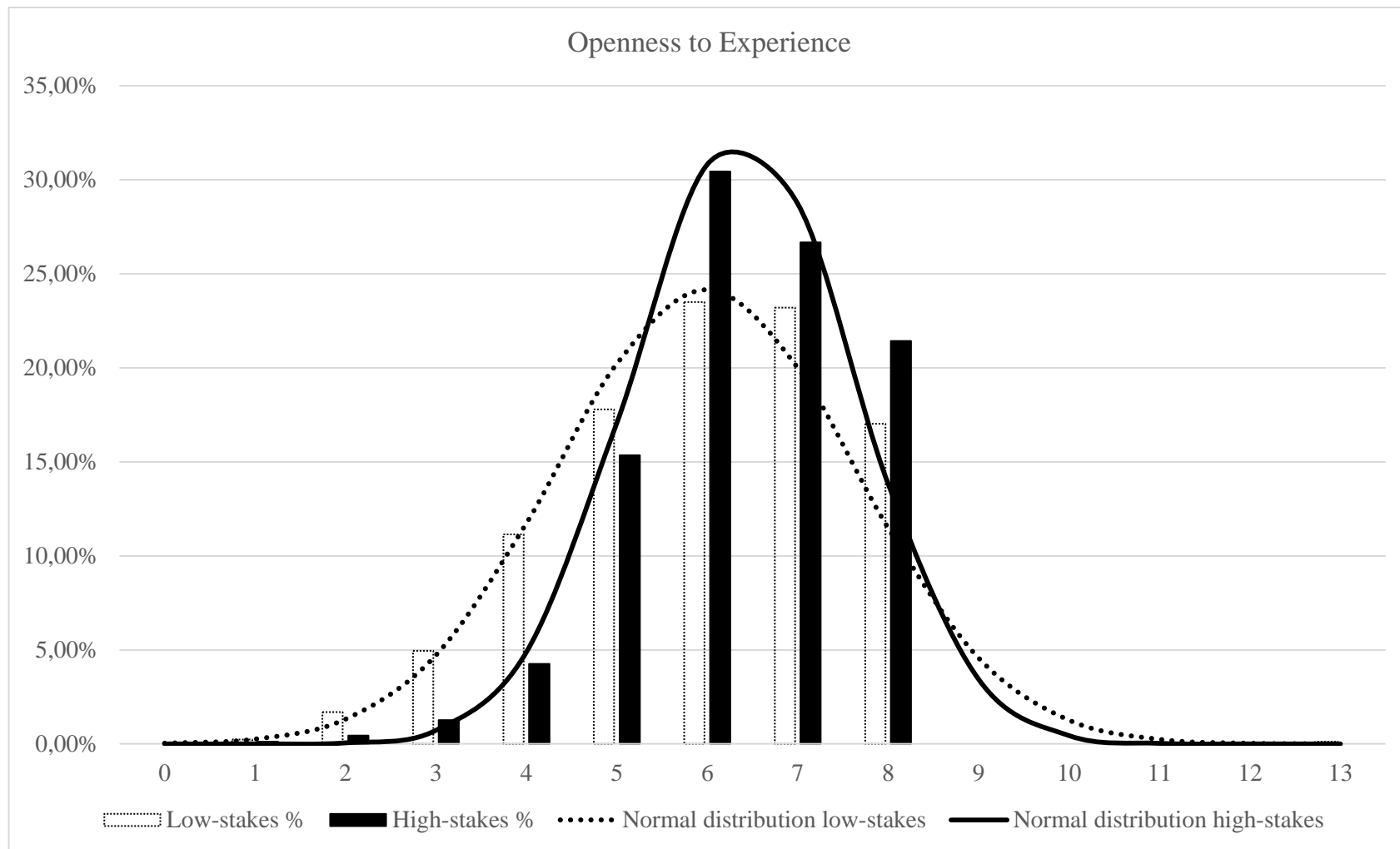


Figure 2.5. Distribution of Openness to Experience (Study 2).

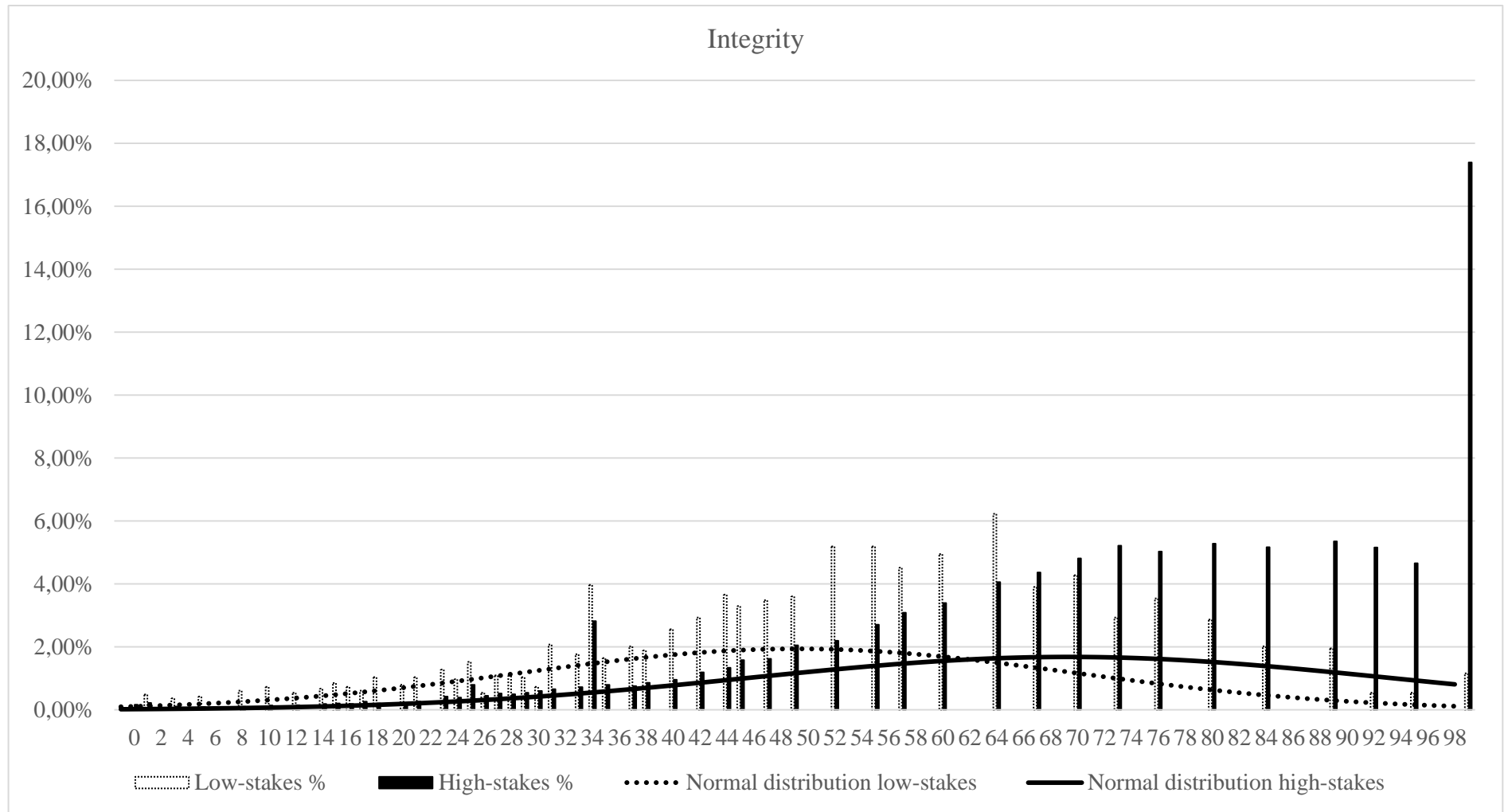


Figure 2.6. Distribution of Integrity (Study 2).

high-stakes setting, thus there is a high possibility of the population being negatively skewed. Regarding Extraversion in the low-stakes setting, Z_{gl} was 2.27 meaning there is a high possibility of the population being positively skewed. The same is true for Emotional stability ($Z_{gl} = 8.02$) and Openness to Experience ($Z_{gl} = 10.44$). For Conscientiousness ($Z_{gl} = -.39$) and Integrity ($Z_{gl} = .30$) in the low-stakes setting, Z_{gl} was between -2 and 2, thus any skewness for these two variables seems to stem from sample drawing. In summary, the high-stakes data are all very likely skewed negatively, while the low-stakes data are all skewed either positively or not at all.

Table 2.7

Skewness and Kurtosis of the Scales (Study 2).

Variable	Low-stakes			High-stakes		
	N	Skewness (SE)	Kurtosis (SE)	N	Skewness (SE)	Kurtosis (SE)
Extraversion	1,715	.13 (.06)	3.52 (.12)	35,774	-1.36 (.01)	1.80 (.03)
Conscientiousness	1,715	-.02 (.06)	1.33 (.12)	35,774	-.65 (.01)	.79 (.03)
Emotional Stability	1,715	.47 (.06)	.19 (.12)	35,774	-.25 (.01)	-.54 (.03)
Openness to Experience	1,715	.62 (.06)	7.73 (.12)	35,774	-.62 (.01)	-.57 (.03)
Integrity	1,642	.02 (.06)	-.46 (.12)	34,937	-.57 (.01)	-.57 (.03)

Finally, we used @RISK6 to check for the fitting of a normal and a mirrored Gumbel distribution to our data. Table 8 shows the results. Massey (1951) suggests using the Kolmogorov-Smirnov test for goodness of fit. Note that a lower value means better model fit. As shown in Table 2.8, the low-stakes variables have a better fit to a normal distribution (with the exception of Openness to Experience), while the high-stakes variables

have a better fit to a mirrored Gumbel distribution. Altogether, the findings empirically support H3.

Table 2.8

Normal Distribution and Mirrored Gumbel Distribution Fit Statistics (Study 2).

Variable	Low-stakes		High-stakes	
	K/S Normal Distribution	K/S Mirrored Gumbel Distribution	K/S Normal Distribution	K/S Mirrored Gumbel Distribution
Extraversion	.09	.17	.17	.14
Conscientiousness	.08	.14	.10	.09
Emotional Stability	.12	.14	.13	.12
Openness to Experience	.25	.16	.20	.17
Integrity	.05	.08	.11	.10

2.4.3 Discussion

With this second study, we propose a new methodology for analyzing differences between low- and high-stakes settings. Instead of only looking at means of variables, we utilized variable distributions and skewness to find evidence for response distortion. The data empirically provided support for our hypothesis: the variables in a high-stakes setting were all skewed negatively, while in a low-stakes setting they were skewed positively or not skewed at all. Furthermore, the data in the high-stakes setting resembled best a Mirrored Gumbel distribution, while the data in the low-stakes setting resembled best a Gaussian distribution (with the exception of Openness to Experience).

2.5 General Discussion

To our knowledge this is the first study that examines the usability of personality indicators for giving credits to entrepreneurs in high stakes situations. We extended some issues discussed in the selection literature to entrepreneurs applying for a loan. We present a new methodology to compare low-stakes to high-stakes data through analyzing variable distributions, following a call by Stark et al. (2001). The results suggest that in a real-life selection setting, applicants tend to give different answers personality variables extraversion, conscientiousness, emotional stability, openness to experience and integrity. To test the effects of these changes on rank ordering abilities, we built two simple credit scoring models for predicting the probability of default, one based on low-stakes and the other based on high-stakes data. We then applied it to both high-stakes and low-stakes applicants. The results show that a model based on high-stakes data performs well in a high-stakes context but not in a low-stakes context (and vice versa for the other model). A model built on low-stakes data has predictive power in other low-stakes applications with a gini coefficient of 35%, whereas applying that same model to a high-stakes setting reduces its predictive power to 1.8%. So building predictive models in low-stakes situations, which is typical of scientific studies that rely on volunteers participating in research projects, cannot be validly applied to high-stakes settings such as a loan application: the models will cease to distinguish high from low performers, defaulters from repayers. It is important to note that personality measures can still be valid selection tools in high-stakes settings. Although response distortion may happen in high-stakes situations, we can get gini coefficient of 21% and above. However, the predictive models need to be built from high-stakes situations as well. In other words, even if loan applicants distort their responses in a high-stakes applications, it is possible to build models that reliably predict the outcomes and are useful as tools for selection.

In Study 2 the distribution of these variables in a low-stakes setting resembles best a normal distribution that is very little skewed; the same variables assessed in a high-stakes setting are negatively skewed and are best represented by a Mirrored Gumbel distribution (with the exception of openness to experience).

Thus, there are obvious differences between high- and low-stakes situations in the distributions (Study 2) and validity of personality indicators (Study 1). We believe that our study has practical, methodological, and theoretical implications. The practical conclusion is obvious: One should not attempt to generalize from the general literature (which is usually performed in low-stakes situations) predictors to a high-stakes situation, such as credit selection. Rather, it is necessary to do the validity tests in the real high-stakes situation. Tests for credit selection should be based on data collected from similar applicants in past high-stakes settings. Unfortunately, this creates a bit of a ‘chicken and egg’ problem for practitioners, in that it is difficult to have instruments implemented in a high-stakes setting until they are well-validated, but they cannot be well-validated until they are implemented in a high-stakes setting. Nevertheless, it is clear that this problem cannot be bypassed through low-stakes testing for validation.

The methodological implications lead us to conclude that we have to be much more aware whether or not a study actually is interpreted by the participants as a high or low stake situation. Depending upon this interpretation, the effects of personality factors on success are different. This may imply that meta-analyses should code the articles whether they constitute high- or low-stakes situations. Further, naïve assumptions of generalizability of results may have to be tempered in a number of fields of entrepreneurship. It may be possible to use camouflage techniques like the randomized response techniques to get honest answers (Peeters, Lensvelt-Mulders, & Lasthuizen, 2010) or better techniques of item response testing (Stark et al., 2001).

The theoretical implications are more complex. In any case, the lazy idea that poor micro-business owners with little education are not able to adjust their answers to the demands of the situation has to be laid to rest. We need to have a much better idea of the interpretations of the entrepreneurs. Response distortion clearly happens. But is it only happening when there are high stakes? As we suggested in our introduction, we doubt that. We rather think that people are much more aware and thoughtful of their answers in a high stakes situation. That can have positive as well as negative effects: The positive effects imply that thoughtless answers to questions are much less frequent. The negative effect is that business owners do think about the demand characteristics of the situation and adjust to them. A corresponding concept, a candidate's ability to identify criteria (ATIC) of selection procedures, is described by König, Melchers, Kleinmann, Richter, & Klehe (2007). The authors show that a candidate's ability to identify which criteria are assessed in a selection procedure predict the candidate's performance. We suggest that this may be stronger in the area of personality than in other areas. But we also believe that an adjustment to the demand characteristics is probably also important in every situation where answers might have positive or negative consequences. This may have implications on how answers are given regarding issues of innovation, profitability, political realm in the area of entrepreneurship, etc.

2.5.1 Strengths and Limitations

One of the strengths of this study is its large sample size ($n = 37,489$) and that real-life data were collected in a high-stakes settings instead of relying on self-reports (such as using social desirability scales with questionable validity) or simulations. Our analysis of the differences of answer in high-stakes and low-stakes settings are unlikely to be contaminated by memory or social desirability effects. Furthermore, in showing that applicants give

different answers depending on the stakes of assessment, we challenge the long-held assumption that models based on low-stakes data also perform well for high-stakes applicants. Finally, we analyzed entrepreneurial performance with a very clear criterion: paying back a loan and comparing defaulters to non-defaulters (Klinger et al., 2013).

This study is based on a sample of entrepreneurs. We believe that the idea of using personality variables for granting credits to entrepreneurs is a very good one and is likely to be even more important in the future, as more and more banks have detected the bottom of the pyramid customers (Prahalad, 2004).

A limitation of this study is that we had to use a between-groups design. Peterson, Griffith, Converse, & Gammon (2011) have criticized this design as it does not allow for the measurement of score changes at an individual level, but we decided to use this design nonetheless in order to uncover differences between low and high-stakes settings rather than looking at individuals and also to prevent memory / retest effects. Moreover, we attempted to deal with this limitation in evaluating our hypothesis with a sample from within one country that included both high as well as low-stakes settings. To address the problem that the low-stakes sample only included people who already received a loan but the distributions of the high-stakes setting included both financed and rejected applicants, we performed a robustness test in only including the lent-to population in both settings. Sizes and directions of the effects stayed the same with one exception: for openness to experience, in the high-stakes setting the data resembled best a normal distribution instead of a mirrored Gumbel distribution.

2.5.2 Conclusion and Implications

Our study shows that response distortion plays a role in business people applying for credits though this may not be the necessary results of intentional faking. Researchers as well as practitioners should not use data assessed in a low-stakes context for high-stakes application settings but rather keep the stakes constant throughout studies. Selection models

can be effectively applied in high-stakes settings where there are strong incentives for response distortion, but only when the data have been built on data gathered in an equivalent setting. The traditional approach of gathering data and validating psychometric instruments in low-stakes research settings and then applying them directly to high-stakes settings may be not valid.

CHAPTER 3

Comparing an Action-Oriented with a Knowledge-Based Training in Improving Entrepreneurial Skills in a Developing Country

3.1 Abstract

This study contributes to entrepreneurship education literature by comparing two different treatment methods based on the theory of personal initiative (PI). PI is of crucial importance for entrepreneurs and related to entrepreneurial success. With a sample of $N = 47$, we conducted a randomized controlled trial study with an action-based, a knowledge-based and a non-treatment control group. The results show that the knowledge-based training mainly increases PI knowledge while the action-based training mainly increases PI behavior. Both treatments had a small but significant positive effect on participants' overall success. We were unable to find a mediating effect of training participation through PI on overall success, mainly caused by low power due to the small sample size. Results and implications are discussed.

3.2 Introduction

Entrepreneurship education is on the rise. There is now a fair amount of studies that focus on entrepreneurship education. We include under this topic all educational attempts to improve the skills or change the mindsets of entrepreneurs to increase start-up rates. Unger, Rauch, Frese, & Rosenbusch (2011) found a positive relationship between human capital and success of entrepreneurs in their meta-analysis. A recent meta-analysis by Jun Bae et al. (2014) has shown a significant yet small effect of entrepreneurship education on

entrepreneurial intentions, but the effect vanishes when controlling for pre-education entrepreneurial intentions. Also, Glaub & Frese (2011) as well as McKenzie & Woodruff (2013) found substantial heterogeneity and methodological flaws (such as not using a randomized control group) among many studies on entrepreneurship teaching. McKenzie & Woodruff (2013) call for studies extending the work of Drexler, Fischer, & Schoar (2014) who tested two different treatments of teaching financial accounting skills to entrepreneurs. We follow that call with account to the criticism of Glaub & Frese (2011) in presenting a randomized controlled trial study amongst existing business owners with two different treatments: one group received an action-based training, one group received a knowledge-based training, and we additionally used a non-treatment randomized control group.

3.3 Theory

There is important data that entrepreneurship is a source of employment, innovation, and general economic prosperity (Autio, 2005; Walter et al., 2005; Reynolds et al., 2005; Kuratko, 2003). Job creation through business ownership is especially important in developing countries where the number of large companies and therefore job opportunities are limited (Walter et al., 2005; Mead & Liedholm, 1998). Furthermore, strengthening the small business sector is one of the best ways to reduce poverty and increase economic growth (Birch, 1987). Strengthening the small business sector can be done by governmental programs or policy changes like simplifying business registration or reducing/eliminating the minimum capital requirement for business owners (The World Bank, 2010).

Another option to strengthen the small business sector is through business ownership trainings. de Mel, McKenzie, & Woodruff (2014) as well as Martin, McNally, & Kay (2013) have shown that business ownership trainings are a useful tool to promote business

ownership. This is especially true for trainings using an active learning approach (Martinez et al., 2010; Oosterbeck, Praag, & Ijsselstein, 2010; Barr, Baker, & Markham, 2009; Rasmussen & Sørheim, 2006; Honig, 2004; Fiet, 2001b; Gorman, Hanlon, & King, 1997). Yet, as shown in Glaub & Frese's (2011) review, evaluation of business ownership trainings has suffered from flaws of methodological issues like the absence of a randomized control group. We address this issue in presenting a randomized controlled experiment with three different groups of owners: a knowledge-based training, an action-based business training, as well as a control group.

The two treatments were based on the theory of personal initiative. Kuhn (1970) argues that “theory is the most practical thing that we can teach to students” (as cited in Fiet, 2001a, p. 1). An important theory for business ownership is the theory of personal initiative (PI). PI is positively correlated with business ownerial activity and success (Rauch & Frese, 2007; Krauss, 2003; Utsch & Rauch, 2000; Koop, De Reu & Frese, 2000). Frese, Kring, Soose, & Zempel (1996) defined PI as an action characterized by being *self-starting*, *proactive*, and *persistent*.

An action is *self-started* when it is initiated by one self. Being self-starting is of high importance for a business owner as they have no supervisor that instructs them on what to do. They need to decide for themselves what they want to do. Being self-starting also includes being different than others and not following trends. In other words, entrepreneurs that are self-starting look for new ideas instead of sticking to old routines, offer something different than their competitors, and are eager to be the first to act instead of reacting.

Proactive means that an action is long-term- and future-oriented. Being proactive is of high importance for a business owner as they have to anticipate future problems and opportunities and prepare for them now (Krauss, 2003).

An action is *persistent* when barriers, setbacks and failures are overcome through keeping up actions, goals and plans and regulating emotions. Persistence is of high importance for a business owner as they have to face and overcome barriers like resource scarcity or failure. PI amongst business owners can be increased through training and mediates the training effect on success (Glaub, Frese, Fischer, Klemm, 2014). Therefore we based both the knowledge- and the action-based training on the theory of PI.

The aim of our knowledge-based training was to increase the participants' PI knowledge (e.g. that the participants understood the theory of PI and why it is helpful for business ownership). Acquisition of declarative knowledge precedes higher order skill development (Kraiger, Ford, & Salas, 1993). Gagné (1984) claims that learning outcomes of trainings are knowledge, attitudes and motor skills. Consequently, the traditional approach in educating business ownership has been teaching business management skills like marketing, financing and so on (Solomon & Fernald, 1993), usually utilizing lectures and case studies (Ahiarah, 1989). However, Rideout & Gray (2013) state that “today’s teaching methods are still overly reliant on [...] lectures and case studies, perhaps with a guest speaker thrown in. As in the past, curricula typically include opportunity identification, managing growth, marketing, finance, and business planning” (p. 332). We thus offered a knowledge-based training consisting of lecture and case studies, with our curriculum focused on the theory of personal initiative instead of business knowledge.

To compare the effects of this knowledge-based training on entrepreneurial success we utilized a second treatment group that received an action-based training. Gielnik et al. (2014) provided evidence for the positive impact of an action-based training on students successfully starting and running a business. Action training consists of different components: development of an action-oriented mental model, learning by action, matching training task and job task, and feedback. To assist the business owners in developing an action-oriented

mental model, we taught the participants action principles instead of mere theory. Action principles are “rules of thumb” that tell the participants what kind of behavior to show in specific situations (e.g. “Look actively for information. Don’t wait until people tell you” for information seeking). These behaviors might be contrary to old routines of the entrepreneurs (e.g. not actively looking for information). As newly acquired behavior competes with old routines (Frese & Zapf, 1994) and needs to be routinized in order to be sustainable, the training contained practical exercises to favor the use of the new behavior.

The practical exercises for the action-based training were based on the same case studies that we utilized in the knowledge-based training (e.g. analyzing the daily routine of a shop owner for reactive behavior and working out more favorable, alternative actions), but included an active part for the participants. First, they had to analyze the different cases regarding several aspects of PI in small groups. Second, the analysis of the participants were presented to and discussed with the whole training group. Third, the participants had to transfer what they had learned from the case studies and group discussions to their own business through repeating the same exercise personally (e.g. analyzing their own daily routine for reactive behavior and then working on alternative actions). Transfer from training task to job task was ensured through the use of identical elements in training and transfer situation (Baldwin & Ford, 1998). This means that the business owners had to use what they learned through the case studies with the same methodology for their own enterprise. Feedback was provided by the trainers who were experts in the field of PI as well as by the other participants regarding positive (what did the business owners learn) and negative (what could be improved) aspects.

Action-based trainings have been shown to lead to successful business creation (Gielnik et al., 2014) as well as to increase success amongst existing business owners (Glaub et al., 2014). A theoretical framework for action-based trainings is action regulation theory.

Action regulation theory explains how people get from an idea or an intention to a concrete action. This is important as many people fail to derive actions from their intentions (Brandstaetter, Heimbeck, Malzacher, & Frese, 2003; Davidsson & Honig, 2003; Gollwitzer, 1999), for example entrepreneurs may know that they need to be active but might not be successful in doing so (Glaub et al., 2014). Action regulation theory states that the translation of an intention into an action needs processes of sequential and hierarchical regulation (Frese & Zapf, 1994).

Sequential regulation implies that an individual needs goal-setting, information seeking, planning, and monitoring / feedback to act. It is important to know that these steps do not necessarily need to occur in order, but they need to be aligned to result in an action (Glaub et al., 2014). Hierarchical regulation means that higher level goals (e.g. introducing a new product) or abstract thoughts need to be connected to lower level behaviors (e.g. using muscles to strike a key / type a word) in order to cause action (Frese, 2009). This connection can be done through repeated linkage of operational action principles with newly acquired behavior in a learning-by-doing approach (Glaub et al., 2014). Action also facilitates learning as people are active learners (Frese & Zapf, 1994), an action-based training approach has been shown to be useful in teaching various skills and abilities (Gielnik et al., 2014; Glaub et al., 2014; Frese, Beimel, & Schoenborn, 2003; Ford, Kozlowski, Kraiger, Salas, & Teachout, 1997). We used action regulation theory as framework for designing our action-based training through teaching the parts of the action sequence (goal-setting, information seeking, planning, and monitoring / feedback) and connecting abstract thoughts (action principles) to newly acquired behavior through exercises. It is hard for people to acquire new behaviors as newly acquired behavior competes with old routines. Participants of the action-based training had the chance to practice the newly acquired behaviors in the training.

The aim of our action-based training was to increase the participants' PI behavior (e.g. that the business-related behavior they showed was self-started, proactive and persistent). We used an action-based approach as business ownership requires action. Almost every definition of entrepreneurship known to us includes some form of action or active behavior (Frese, 2009). Already Schumpeter (1934), the pioneer of entrepreneurship research, stated that the trademark of entrepreneurship is an active approach. McMullen & Shepherd (2006) claim that a business owner's action should be the starting point for theorizing in entrepreneurship. Shane & Venkataraman (2000) define business ownership as the identification and exploitation of business opportunities. Frese (2009) offers an action theory perspective on entrepreneurship, explaining why business owners need to be active and offering a solid theoretical foundation for the role of action in the field of entrepreneurship.

Comparing a knowledge-based training to an action-based training, we suggest that both training methods should lead to an increase in the participants knowledge of PI compared to the control group. There should be a difference between the knowledge- and the action-based training regarding PI behavior. The participants of the action-based training experienced the sequential and hierarchical regulation to facilitate action following action regulation theory, while the participants of the knowledge-based training only acquired the abstract thoughts of PI and its importance for entrepreneurship. Thus, participants of the action-based training should be able to demonstrate more PI behavior. Participants of the knowledge-based trainings should be able to connect their experience with the things they learned, but did not have the chance to routinize new behaviors in the training. Therefore both trainings should have an effect on business success, but the effect should be bigger for the action-based training caused by higher overall PI in this group. This leads to the following hypothesis:

H1: PI knowledge increases for both training groups compared to the control group.

H2: PI behavior increases for the action-based training group only.

H3: Business success is increased for both training groups with a higher increase for the action-based training group.

H4: The effect of training participation on business success is mediated through PI behavior for the action-based training group and through PI knowledge for the knowledge-based training group.

3.4 Method

3.4.1 Design

We conducted the study using a control group and a pretest / posttest design to control for effects of self-selection, history, maturation, and testing (Cook, Campbell & Peracchio, 1990). The participants in the control group received 10.000 Ugandan Shilling (~4 USD) for answering the interview and the questionnaires. The two treatment groups (knowledge-based training and action-based training) did not receive any money. Both treatments were based on the exact same content, but since the action-based training included elements of action this training was longer (three days) than the knowledge-based training (one day). Data were collected before the beginning of the training (T1) and twelve months after the training (T2).

3.4.2 Sample

Participants were sampled using two different strategies. First, we cooperated with the Uganda Small Scale Industry Association (USSIA), the Uganda Women Business owners Association Limited (UWEAL) and the Business ownership Centre at Makerere University Business School to get contacts of business owners. Furthermore, we made random walk-ins

through different markets in Kampala and asked to speak with the owner of the respective business. Participants were randomized before they were told about the research project and their role. Action- and knowledge-based training participants were given information about their program; control group participants were informed that they would receive a monetary compensation for being part of the research project. Through our strategies we wanted to ensure to cover business owners from different lines of industry and also of different businesses ages. Table 3.1 provides descriptive information about action training, knowledge training and control group.

Our initial sample consisted of 85 business owners who were randomly assigned to the action-based (24) and the knowledge-based (25) training as well as the control group. At T2, we were able to collect data from 62 participants. Of the remaining 23 participants, five refused to take further part in the study (since they had already received the training and their certificate, or the compensation did not seem attractive enough to them anymore). We were unable to allocate 17 participants in spite of collecting a lot of additional contact information, for example phone numbers of parents or friends. Usually, this additional information helps to allocate study participants and has been shown to be effective, for example in Glaub et al. (2014). Regarding the 63 participants reached at T2 we had to remove four datasets due to clerical errors (duplicate answers, probably caused by overwriting an old interview with a new ID). Nine of the participants were not able to report sales data; it turned out that they were employees who had been interested to participate in the training and, therefore, did not tell us that they were not the real owners of the businesses. We were aiming at business owners with our study as only they can implement newly acquired principles and behaviors to their firm, thus we had to remove these nine participants from our datasets as well. Three datasets had to be removed due to extreme outliers in the scatter plot ($+2.5$ SD for employees, $M = 12.70$ ($SD = 21.65$) and sales, $M = 115,273,825.00$ or 115.27 Million UGX ($SD =$

328,973,858.50). One participant reported 124 employees, one reported sales of 1,204 Million UGX, and one reported 68 employees and sales of 462 Million UGX.

Our final sample included 47 business owners, 20 in the control group, 15 in the knowledge-based training, and 12 in the action-based training.

3.4.3 Treatment

Table 3.2 offers an overview of the two training programs extending the work by Glaub et al. (2014) whose training we used as basis for our training. Since Berge, Bjorvatn, Juniwaty, & Tungodden (2012) found that different trainers can have an impact on attendance rate, participants' evaluation of training quality and knowledge of training content, we used the same professional trainer for both treatments.

Table 3.1

Sample Characteristics.

	Action- Based Training	Knowledge- Based Training	Control Group
N	12	15	20
Sex = Male	5 (41,6%)	3 (20%)	4 (20%)
Parents Business Owners = Yes	5 (41,6%)	7 (46,6%)	7 (35%)
Married	6 (50%)	10 (66,6%)	6 (30%)
	<u>M (SD)</u>	<u>M (SD)</u>	<u>M (SD)</u>
Age	42.5 (14.5)	41.9 (12.0)	39.1 (13.2)
Children	2.5 (2.9)	2.7 (1.5)	2.1 (1.6)

3.4.4 Measures

Data collection consisted of a structured interview and a questionnaire in English at both measurement waves (T1 and T2). We conducted a thorough interviewer training with the interviewers before data collection. Notes were taken electronically during the interviews and later rated by two independent PI experts with good ICCs ranging from .73 to .97.

Background Measures. As background measures, we assessed the participants age, sex, their marital status, the number of children and whether their parents had been business owners via interview.

Reactive Measures. We assessed affective reactions, perceived usability and transfer motivation as the participants reactive measures. Affective reactions were assessed via questionnaire using Kunin's (1955) face scale ranging from 1 to 7 (asking "How satisfied were you with the content of the training?" and correspondingly for delivery and overall satisfaction).

For usability, we asked participants "Do you think the part 'self-starting and innovation' is useful for your business?" and correspondingly for all other training parts, using a Likert scale ranging from 1 ("Not at all") to 5 ("Very much").

For transfer motivation, we asked participants "To what extend do you think that after this training you will look for more information from different sources than you did before?" and correspondingly for all other training parts, using a Likert scale ranging from 1 ("Not at all likely") to 5 ("Very likely").

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

Table 3.2

Overview of the two training programs.

Content	Action-Based Training	Knowledge-Based Training
Goals	<p>PI: Self-starting</p> <p><i>Action principles:</i> Introduce something new</p> <p><i>Model:</i> Two case studies – one entrepreneur that sets self-starting goals, one entrepreneur that is reactive</p> <p><i>Exercise:</i> Analyze case studies for self-starting goals / reactive behavior</p> <p><i>Application to own business:</i> Set self-starting goal for own business</p> <p>PI: Proactive</p> <p><i>Action principles:</i> Set long term goals with a range of up to two years</p> <p><i>Model:</i> Case study “Venus’ restaurant” – entrepreneur with proactive long-term goals and short-term goals</p> <p><i>Exercise:</i> Analyze case study “Venus’ restaurant”: Set additional proactive long-term goals for Venus</p> <p><i>Application to own business:</i> Set long-term goals for own business</p> <p>PI: Persistent</p> <p><i>Action principles:</i> Keep goals when obstacles occur, try other ways</p> <p><i>Model:</i> 1) Two case studies: one self-starting business owner being persistent and one reactive business owner; 2) Case study “overcoming barriers” - business owner who is highly persistent</p> <p><i>Exercises:</i> Group work based on the case study “metal fabrication & repair” – use problem solving techniques</p>	<p><i>Principles:</i> A successful entrepreneur introduces something new</p> <p><i>Model:</i> Two case studies – one entrepreneur that sets self-starting goals, one entrepreneur that is reactive</p> <p><i>Principles:</i> A successful entrepreneur sets long term goals with a range of up to two years</p> <p><i>Model:</i> Case study “Venus’ restaurant” – entrepreneur with proactive long-term goals and short-term goals</p> <p><i>Principles:</i> A successful entrepreneur keeps goals when obstacles occur, tries other ways</p> <p><i>Model:</i> 1) Two case studies: one self-starting business owner being persistent and one reactive business owner; 2) Case study “overcoming barriers” - business owner who is highly persistent</p>

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

Information Seeking	PI: Self-starting	Self-	<p><i>Action principles:</i> Look actively for information, change your environment</p> <p><i>Model:</i> Three case studies on innovation (product, process, advertising), eight case studies on sources of information for innovative ideas of business owners from Africa</p> <p><i>Exercise:</i> 1) Examples presented by participants of how to use various sources of information actively;</p> <p>2) Exercise “core competencies” to identify future opportunities;</p> <p>3) Use of creativity techniques to create opportunities; develop self-starting goals from these opportunities</p> <p><i>Application to own business:</i> Think of how to actively use sources of information for the personal project, create innovative ideas</p>	<p><i>Principles:</i> A successful entrepreneur actively looks for information, changes his/her environment</p> <p><i>Model:</i> Three case studies on innovation (product, process, advertising), eight case studies on sources of information for innovative ideas of business owners from Africa</p>
	PI: Proactive		<p><i>Action principles:</i> Look for information about future opportunities and problems</p> <p><i>Model:</i> Case study “the shoemaker”- entrepreneur that looks for information about future opportunities</p> <p><i>Exercise:</i> Group work based on case study “the shoemaker”: consider potential future problems</p> <p><i>Application to own business:</i> Consider potential future opportunities and problems for personal project</p>	<p><i>Principles:</i> A successful entrepreneur looks for information about future opportunities and problems</p> <p><i>Model:</i> Case study “the shoemaker”- entrepreneur that looks for information about future opportunities</p>

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

PI: Persistent	<p><i>Action principles:</i> look for information that is difficult to get and rare</p> <p><i>Model:</i> Case study “overcoming barriers” - business owner who is highly persistent in getting information</p> <p><i>Exercise:</i> Collect sources of information that are difficult to get and rare</p> <p><i>Application to own business:</i> Consider which rare sources of information are applicable for your personal project</p>	<p><i>Principles:</i> A successful entrepreneur looks for information that is difficult to get and rare</p> <p><i>Model:</i> Case study “overcoming barriers” - business owner who is highly persistent in getting information</p>
-----------------------	---	--

Planning	PI: Self-starting	<p><i>Action principles:</i> your plan must imply that you can execute it without waiting for things to happen</p> <p><i>Model:</i> 2 Case studies – a self-starting business owner with an active plan and a reactive business owner</p> <p><i>Exercise:</i> Group work based on the case study “designer of clothes”- develop an active plan</p> <p><i>Application to own business:</i> Plan self-starting actions towards the goal of your personal project, discuss them in pairs</p>	<p><i>Principles:</i> The plan of a successful entrepreneur implies that s/he can execute it without waiting for things to happen</p> <p><i>Model:</i> 2 Case studies – a self-starting business owner with an active plan and a reactive business owner</p>
	PI: Proactive	<p><i>Action principles:</i> Develop a plan for future opportunities and problems</p> <p><i>Model:</i> 2 Case studies - 1 self-starting business owner who has a long-range plan and 1 reactive business owner who doesn't plan</p> <p><i>Exercise:</i> Group work based on the case study “designer of clothes”- develop a plan for future problems</p>	<p><i>Principles:</i> A successful entrepreneur develops a plan for future opportunities and problems</p> <p><i>Model:</i> 2 Case studies - 1 self-starting business owner who has a long-range plan and 1 reactive business owner who doesn't plan</p>

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

PI: Persistent

Application to own business: Think about what possible future opportunities and problems might occur, then make plans for personal project to meet them

Action principles: anticipate potential barriers and develop a back-up plan, return to plan quickly when disrupted, do not let barriers distract you

Model: Case study “overcoming barriers” of business owner who returns to plan quickly when disrupted

Exercise: Group work based on the case study “designer of clothes”- discuss future problems and develop ideas how to respond to them to protect the designers’s plans

Application to own business: Develop back-up plans for the identified future problems of the personal project

Principles: A successful entrepreneur anticipates potential barriers and develops a back-up plan, returns to plan quickly when disrupted, does not let barriers distract you

Model: Case study “overcoming barriers” of business owner who returns to plan quickly when disrupted

Monitoring & Feedback

PI: Self-starting

Action principles: go and actively gather feedback. Don’t wait until somebody gives it to you.

Model: 2 Case studies: 1 self-starting business owner who actively looks for feedback and 1 reactive business owner

Exercise: Group work based on the case study “designer of clothes” - select sources for feedback and think about how to use them actively

Application to own business: Use list “sources of information” and plan how to get feedback for personal project

Principles: A successful entrepreneur actively gathers feedback, doesn’t wait until somebody gives it to him / her.

Model: 2 Case studies: 1 self-starting business owner who actively looks for feedback and 1 reactive business owner

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

PI: Proactive	<i>Action principles:</i> does your product / service meet future needs? <i>Model:</i> Case study of Nokia <i>Exercise:</i> Group work based on case study “designer of clothes” - develop pre-signals for potential problems <i>Application to own business:</i> Develop pre-signals for personal project	<i>Principles:</i> A successful entrepreneur makes sure his/her product / service meets future needs? <i>Model:</i> Case study of Nokia
PI: Persistent	<i>Action principles:</i> Look for feedback that is rare and difficult to get <i>Model:</i> Specific case study “overcoming barriers” of business owner who is highly persistent <i>Exercise:</i> Group work based on the case study “metal fabrication & repair” – use problem solving techniques	<i>Principles:</i> A successful entrepreneur looks for feedback that is rare and difficult to get <i>Model:</i> Specific case study “overcoming barriers” of business owner who is highly persistent

Learning Measures. To measure the participants PI knowledge, we used a multiple choice test developed by Glaub et al. (2014) with four items. The items stated a situation for a fictional business owner (e.g. “Mr H. wants to set a goal for his business. If he showed personal initiative: which goal would he set?”) and ended with four options out of which one was the correct answer (e.g. “introduce a new product competitors don’t sell / copy the product range of the competitors / keep the product range the same / reduce the product range”). The participants’ correct answers were summed to form the index of PI knowledge.

Behavior-based Measures. To measure the participants PI behavior, we assessed quantitative PI behavior (how high their behavior was on initiative) and qualitative PI behavior (to what extent their behavior was original or new and differed from their competitors and common approaches). We assessed quantitative and qualitative PI behavior in asking about two situations where the owners could show PI behavior. One situation addressed the planning of the business owner for the next twelve months (“planning situation”) and one addressed the activities the business owner had actually done in the last twelve months (“factual situation”).

Specifically we asked the participants “Within the last twelve months, have you introduced any changes (e.g. new or more advertising, new products or services, new branches etc.) in your work/business?” (factual situation) respectively “Within the next twelve months, are you planning to introduce any changes (e.g. new or more advertising, new products or services, new branches etc.) in your work/business?” (planning situation). The interviewers were instructed to use prompts and ask for further information about the changes in order to assess the level of PI that was included in the changes, for example why they introduced the changes and if they had been told to do so. Once they stopped reporting changes, the interviewers asked “Anything else?” for once. When the participants did not report more changes, the next question was asked.

The coding for quantitative PI was done in the following way: the reported activities were rated with 0 for a too abstract behavior description (e.g. “get more customers”), 1 for a rough description and 2 for a detailed description of the participants’ behavior. We then summed the ratings for all reported changes to form our quantitative PI scale to get an indicator for how active the participants had been (if s/he reported more activities, the score should be higher for quantitative PI) and used the mean of the two raters (ICCs: T1 planning situation = .86, T1 factual situation = .93; T4 planning situation = .96, T4 factual situation = .95).

To measure the participants qualitative PI, we rated the reported activities on a scale from 1 to 5 where “1” was given for behavior low in PI that was reactive. “5” was given for a detailed behavior description that was self-starting, proactive and persistent (e.g. “bought an own transportable bed to do massages because the clients I visited had uncomfortable beds”).

We used the mean of the two raters to form our qualitative PI scale (ICCs: T1 planning situation = .83, T1 factual situation = .89; T4 planning situation = .78, T4 factual situation = .73).

Success Measures. To measure the participants’ success, we used two different measures: number of employees and sales. We assessed number of employees via interview, asking the participants how many full- and part-time employees they had. We calculated the total number of employees with the formula $number\ of\ employees = full-time\ employees + 0.5 * part-time\ employees$. We assessed sales using a proxy proposed by McPherson (1998) asking participants on sales for the last year in a good, bad, and average month. We then asked participants to report how many good, bad and average months they had had within the last year. Out of these reports we calculated the sales level of the past year (logarithm scale). We formed our *overall success* scale out of the *number of employees* and the *logarithm of the*

sales level (intercorrelations were good at T1, $r = .44$, $p < .01$ and at T2, $r = .33$, $p < .05$) to enhance reliability.

3.5 Results

Due to unexpected loss of participants, we have a low power in this study. Thus, it is necessary to interpret $p < .10$ to avoid making a type II error (failing to reject the null hypothesis when it is false) due to low power. To check for randomization, we used an analysis of variance (ANOVA) as robustness test for all variables at T1. The ANOVA was significant only for PI behavior at T1, therefore we used PI Behavior at T1 as well as line of industry as covariate in our analyses.

Table 3.3 presents the intercorrelations of the study variables. First of all, one can see that our binary variables for action-based and knowledge-based training correlated at least marginally significant with the variables of interest (always tested against the control group coded as 0): Both training groups correlated with PI knowledge, PI behavior, number of employees and overall success at T2. The knowledge-based training group also showed a marginally significant correlation with logarithm of sales at T2.

3.5.1 Reaction Measures

Table 3.4 shows the affective reactions, the perceived usability and transfer motivation of the participants of both trainings. The reactions show that the participants of both groups were very satisfied with training content and delivery as well as overall (M between 6.7 and 6.9 on Kunin's face scale from 1 to 7). Both groups rated the usability and their transfer motivation very high (M between 4.47 and 4.82 on a Likert scale from 1 to 5). There was no obvious difference between both the action-based and the knowledge-based training in their

respective reaction measures, and a t-test we conducted to compare both groups was not significant for all reaction measures. Thus we conclude that there was no difference between the action-based and the knowledge-based training regarding their reaction measures.

Table 3.4

Reaction Measures of the Training Groups.

Variable	Action-based Training	Knowledge-based Training
	M (SD)	M (SD)
Satisfaction /w Content (Scale 1-7)	6.73 (.47)	6.92 (.28)
Satisfaction /w Delivery (Scale 1-7)	6.91 (.30)	6.77 (.44)
Overall Satisfaction (Scale 1-7)	6.73 (.47)	6.77 (.44)
Perceived Usability (Scale 1-5)	4.82 (.31)	4.80 (.24)
Transfer Motivation (Scale 1-5)	4.47 (.45)	4.62 (.26)

Chapter 3 – Comparing an Action-Oriented with a Knowledge-Based Training

Table 3.3

Intercorrelations of the study variables.

Variable	N	M	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
1. action-based group (1 = action-based)	32	.38	.49																				
2. knowledge-based group (1 = knowledge-based)	35	.43	.50																				
3. Age	47	40.85	13.00	.13	.12																		
4. Gender (1 = male)	47	.26	.44	.23 ⁺	.00	-.04																	
5. Married	47	.47	.50	.20	.36*	.21 ⁺	.14																
6. Number of Children	47	2.38	2.00	.10	.21	.67**	-.16	.51**															
7. Parents Business Owner	47	.40	.50	.07	.12	-.13	-.09	.01	-.12														
8. Industry = Aggricultural	47	.15	.36	-.03	.22	.15	-.25*	-.03	.19 ⁺	.02													
9. Industry = Commerce	47	.47	.50	-.55**	-.12	-.11	-.26*	-.20 ⁺	-.14	.27*	-.39**												
10. Industry = Production	47	.17	.38	.37*	-.06	.12	.12	.26*	.26*	-.14	-.19	-.43**											
11. Industry = Service	47	.21	.41	.30*	-.02	-.11	.41**	.03	-.23 ⁺	-.22 ⁺	-.22 ⁺	-.49**	-.24 ⁺										
12. PI Knowledge T1	44	2.32	.86	.11	-.08	.18	-.17	-.02	.16	-.00	.13	-.17	.10	-.01									
13. PI Knowledge T2	40	2.40	.87	.32*	.32*	.00	-.09	.27*	.10	.00	-.06	-.11	.09	.10	.34*								
14. PI Behavior T1	47	1.75	.88	.19	.43**	.29*	-.09	.15	.17	.03	.30*	-.21 ⁺	-.18	.16	-.04	.06							
15. PI Behavior T2	45	2.02	.95	.82**	.33*	.10	.06	.28*	.12	.17	.06	-.43**	.16	.31*	.12	.22 ⁺	.17						
16. Number of Employees T1	47	6.13	5.60	.51**	.32*	.41**	.25*	.19 ⁺	.25*	-.10	.18	-.45**	.35**	.07	.21 ⁺	.06	.21 ⁺	.30*					
17. Number of Employees T2	46	7.17	7.91	.63**	.57**	.30*	.27*	.24 ⁺	.20 ⁺	-.03	.15	-.34**	.30*	.01	.06	.21 ⁺	.21 ⁺	.43**	.78**				
18. Logarithm of Sales T1	47	16.67	1.45	-.21	.03	.00	.15	.13	.03	.12	-.12	.12	.01	-.05	.17	-.06	-.06	-.08	.44**	.31*			
19. Logarithm of Sales T2	46	16.65	1.25	-.11	.26 ⁺	.16	.06	.12	.10	.17	.04	.04	.00	-.08	.10	-.23 ⁺	-.09	-.05	.53**	.33*	.71**		
20. Overall Success T1	47	-.11	.73	.05	.19	.20 ⁺	.22 ⁺	.18	.14	.04	.01	-.13	.17	-.00	.22 ⁺	-.01	.06	.08	.78**	.59**	.91**	.74**	
21. Overall Success T2	47	-.09	.74	.28 ⁺	.46**	.26*	.17	.20 ⁺	.16	.11	.10	-.17	.16	-.02	.11	-.03	.07	.22 ⁺	.79**	.77**	.65**	.86**	.82**

Note. ** correlation is significant at the .01 level (1 tailed); * correlation is significant at the .05 level (1 tailed); ⁺ correlation is significant at the .10 level (1 tailed)

3.5.2 Learning, Behavioral & Success Measures

Table 3.5 shows the means and standard deviations for participants PI knowledge, PI behavior and success measures. Notably, the logarithm of sales slightly increased for both training groups while the absolute sales level decreased from T1 to T2. This can be explained through the change in distributions caused by the logarithmizing procedure.

Table 3.5
Learning, Behavioral and Success Measures.

Variable	Action-based training	Knowledge-based Training	Control Group
	M (SD)	M (SD)	M (SD)
PI Knowledge T1	2.50 (.80)	2.17 (.84)	2.30 (.92)
PI Knowledge T2	2.64 (.51)	2.67 (.78)	2.06 (1.03)
PI Behavior T1	.01 (.80)	.38 (.61)	-.28 (.79)
PI Behavior T2	1.01 (.33)	-.11 (.64)	-.58 (.75)
Number of Employees T1	8.58 (4.25)	7.40 (7.13)	3.70 (4.10)
Number of Employees T2	12.91 (10.38)	9.33 (7.29)	2.40 (2.37)
Logarithm of Sales T1	16.14 (1.89)	16.89 (1.08)	16.82 (1.39)
Logarithm of Sales T2	16.26 (1.64)	17.11 (.76)	16.55 (1.22)
Absolute Sales Level T1 (in Million UGX)	34.10 (51.21)	38.12 (53.33)	40.77 (46.94)
Absolute Sales Level T2 (in Million UGX)	32.57 (47.22)	35.00 (27.10)	27.50 (35.83)
Overall Success T1 (z-standardized)	-.14 (.88)	.05 (.76)	-.21 (.62)
Overall Success T2 (z-standardized)	.05 (1.04)	.19 (.59)	-.39 (.54)

H1 states that PI knowledge increases for both training groups. To provide evidence for this hypothesis, we used a repeated measures ANOVA with General Linear Modeling. We found a marginally significant effect of group x time (*Hotelling's* $t = 2.83$, $p < .10$, $\eta^2 = .15$). Figure 3.1 shows the direction of the effect. The findings partly support H1.

H2 states that PI behavior increases for the action-based training group only. To provide evidence for this hypothesis, we used a repeated measures ANOVA with General Linear Modeling. We found a significant effect of group x time (*Hotelling's* $t = 7.74$, $p < .05$, $\eta^2 = .28$) for PI behavior. Figure 3.2 shows the direction of the effect. The findings support H2.

H3 states that Business success increased for both training groups with a higher increase for the action-based training group. To provide evidence for this hypothesis, we used a repeated measures ANOVA with General Linear Modeling. We found a significant effect of group (*Hotelling's* $t = 4.61$, $p < .05$, $\eta^2 = .19$). Figure 3.3 shows the direction of the effect. The findings support H3.

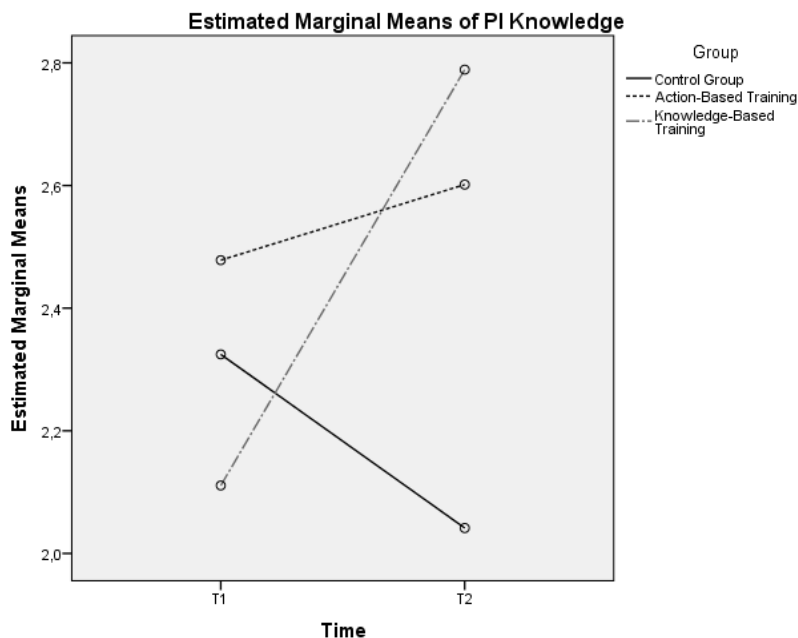


Figure 3.1. ANOVA Results: Estimated marginal means of PI knowledge by group x time.

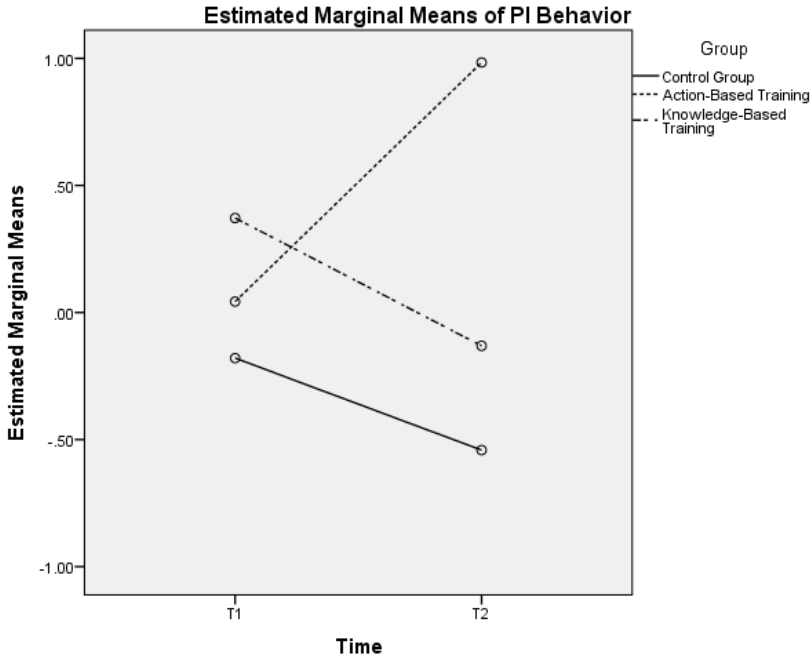


Figure 3.2. ANOVA Results: Estimated marginal means of PI behavior by group x time.

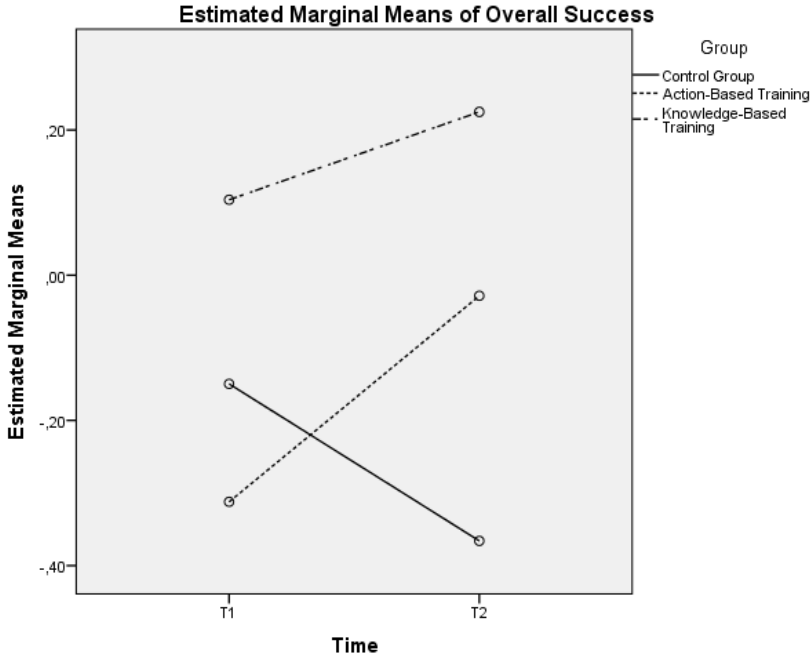


Figure 3.3. ANOVA Results: Estimated marginal means of overall success by group x time.

To provide additional evidence for our hypotheses taking into account the differences at T1 PI behavior, we used a multivariate analysis of covariance (MANCOVA) with PI behavior, PI knowledge and overall success at T2 as dependent variable, the respective variables at T1 as covariates and training group as independent variable. The MANCOVA revealed main effects of training group (*Hotelling's t* = 6.76, $p < .01$, $\eta^2 = .44$) and T1 overall success (*Hotelling's t* = 18.85, $p < .01$, $\eta^2 = .68$). Looking at the between-subjects effects, we found a significant effect of T1 PI knowledge on T2 PI knowledge ($F(1, 29) = 7.43$, $p < .05$, $\eta^2 = .20$), of T1 overall success on T2 overall success ($F(1, 29) = 60.17$, $p < .01$, $\eta^2 = .68$), and of training group on T2 PI knowledge ($F(2, 29) = 3.48$, $p < .05$, $\eta^2 = .19$), T2 PI behavior ($F(2, 29) = 14.40$, $p < .01$, $\eta^2 = .50$), and T2 overall success ($F(2, 29) = 4.19$, $p < .05$, $\eta^2 = .22$). Figures 3.4 through 3.6 show the estimated marginal means of the dependent variables. The findings support H1, H2, and H3.

3.5.3 Mediation of PI

Hypothesis H4 states that the increase in the participants success of action- and knowledge-based training compared to the control group is mediated through PI behavior respectively PI knowledge. Following Hayes & Preacher (2014), we used bootstrapping to provide evidence for the mediation of the training effect on participants success through PI. We used the macro "PROCESS" for SPSS with a multicategorical independent variable as is the case for three groups like in our study (action-based, knowledge-based, control group). We first compared the action-based group against the knowledge-based group and the control group. We used overall success at T2 as dependent variable and PI behavior at T2 as possible mediator with T1 PI behavior and line of industry as covariate. Bootstrapping showed a CI_{95} between -.30 and .79. As the confidence interval did include zero, the data did not provide evidence for a mediation effect of PI behavior for the action-based group.

We then compared the knowledge-based group against the action-based group and the control group. We used overall success at T2 as dependent variable and PI knowledge at T2 as possible mediator with T1 PI behavior and line of industry as covariate. Bootstrapping showed a CI₉₅ between -.40 and .03. As the confidence interval did include zero, the data did not provide evidence for a mediation effect of PI knowledge for the knowledge-based group. Thus, H4 was not empirically supported.

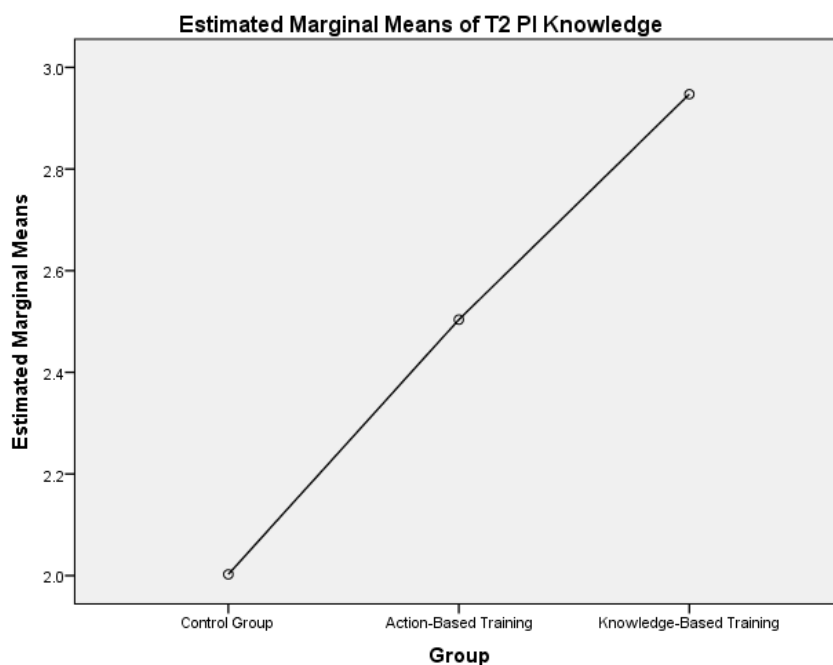


Figure 3.4. MANCOVA Results: Estimated marginal means of T2 PI knowledge by group.

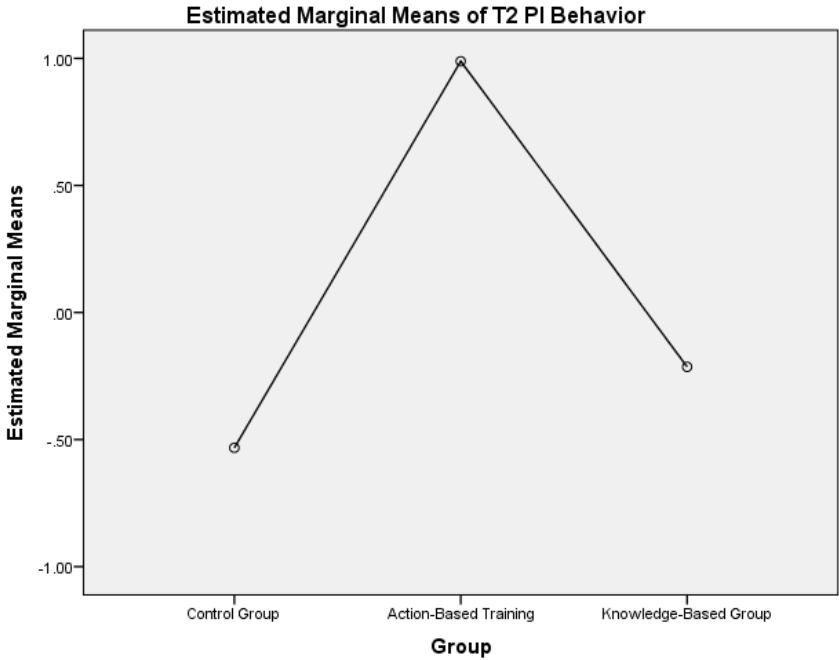


Figure 3.5. MANCOVA Results: Estimated marginal means of T2 PI behavior.

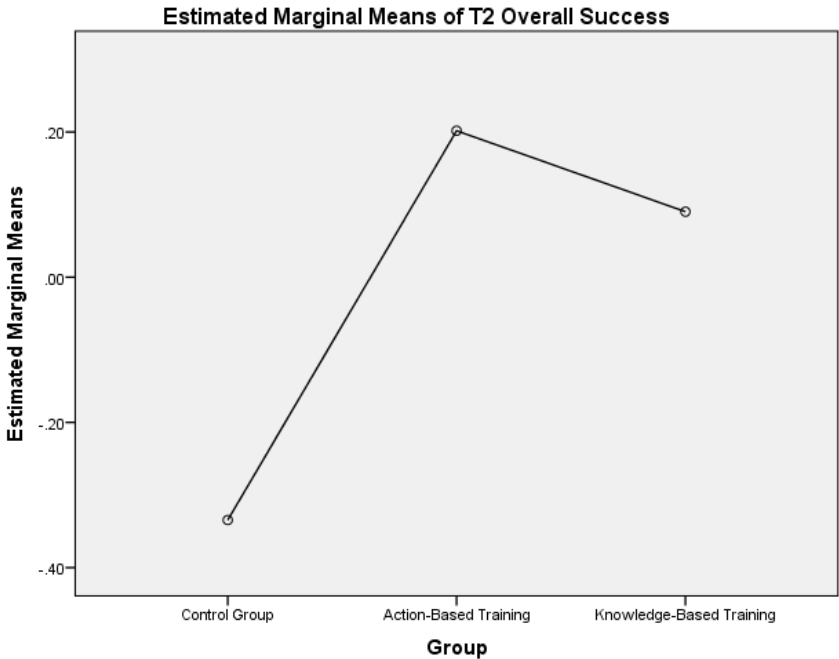


Figure 3.6. MANCOVA Results: Estimated marginal means of T2 overall success.

3.6 Discussion

Our study helps to understand the process of learning among entrepreneurs. We provide evidence for the impact of entrepreneurship education on knowledge and behavior of business owners and on the success of their firms. We do so in presenting two different trainings, one action-based and one knowledge-based, for existing entrepreneurs in Uganda. Many articles of training evaluation literature focus on reaction measures only (McMullan, Chrisman, & Vesper, 2001). We did not find any significant difference between action-based and knowledge-based training, the participants of both training groups were satisfied with what they had received and showed the same transfer motivation to use what they had learned in their businesses. Also, both trainings had a small but significant positive effect on the success of the firms (Cohen's $d = .21$ for both groups compared to T1) while the control group decreased in success (Cohen's $d = -.32$).

For the other measures, we found differences between the trainings: Our MANCOVA shows that the knowledge-based training primarily increased PI knowledge, while the action-based training primarily increased PI behavior. Looking at the absolute numbers, the knowledge group at T2 after the training had a mean of T2 $M = 2.67$ (T1 $M = 2.17$) while the action group had a mean of T2 $M = 2.64$ (T1 $M = 2.50$) compared to the control group with T2 $M = 2.06$ (T1 $M = 2.30$). Glaub et al. (2014) reported $M = 3.06$ in their study for PI knowledge after the training. The action-based training had a large effect on PI behavior (Cohen's $d = 1.71$) and a medium effect on number of employees (Cohen's $d = .57$). The knowledge-based training had a medium effect on PI knowledge (Cohen's $d = .64$), a large but negative effect on PI behavior (Cohen's $d = -.85$), and a small effect on employees (Cohen's $d = .28$). and logarithm of sales (Cohen's $d = .24$).

We did not find evidence for our hypothesis that the effect of training participation on business success is mediated through PI behavior for the action-based training group and through PI knowledge for the knowledge-based training group. We believe that this is caused mainly by low statistical power because we only had N = 12 / N = 15 participants in the action-/knowledge-based training group respectively. As a post-hoc test, we thus calculated the scatter plot of PI behavior and PI knowledge on overall success (figures 3.7 through 3.10). The scatter plot shows that at T2 the participants of the action-based training had higher PI behavior and also a higher range of success (Min -1.58, Max 1.72) than the knowledge-based group (Min -.54, Max 1.77) and the control group (Min -1.46, Max .96). That might speak for a moderating effect (some participants benefit from the training, or, to be exact, from PI behavior, more than others): The higher PI behavior, the wider the range of overall success, so there might be other variables that facilitate using PI behavior to increase success (for example business networks, access to resources etc.).

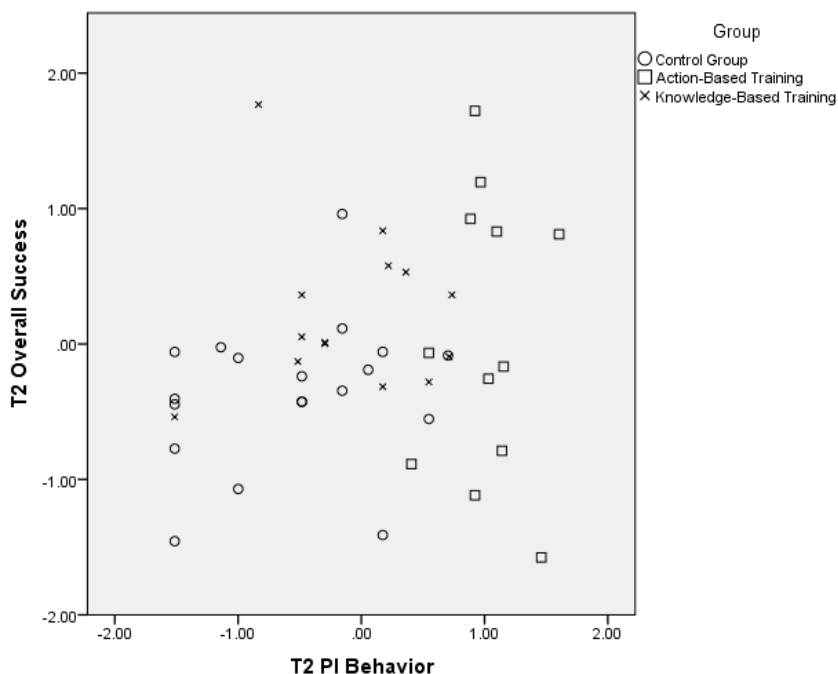


Figure 3.7. Scatter plot of T2 PI Behavior and T2 Overall Success separated by group.

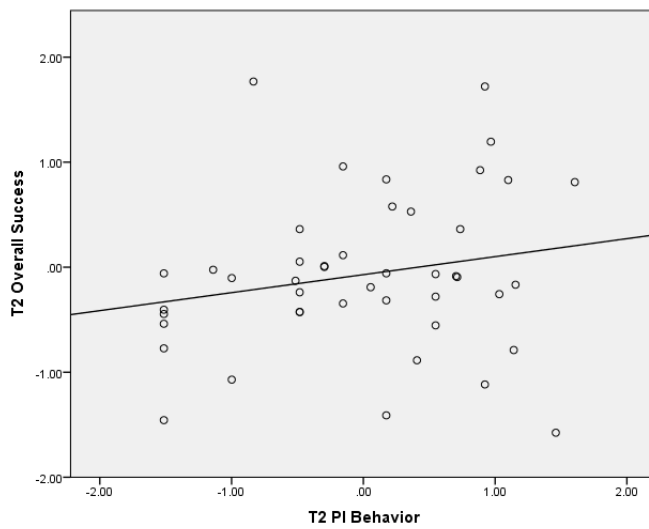


Figure 3.8. Scatter plot of T2 PI Behavior and T2 Overall Success for all participants with regression line.

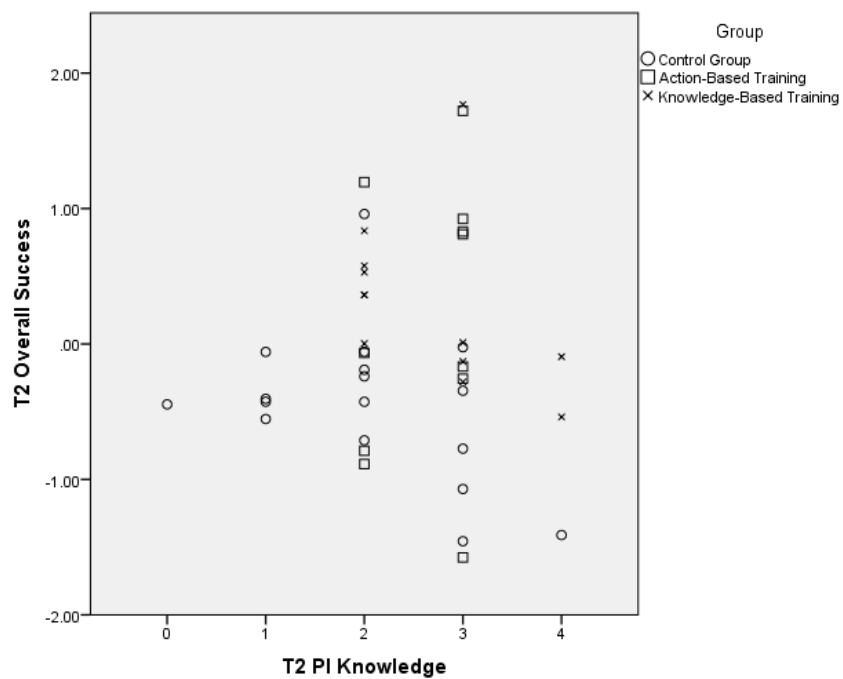


Figure 3.9. Scatter plot of T2 PI Knowledge and T2 Overall Success separated by group.

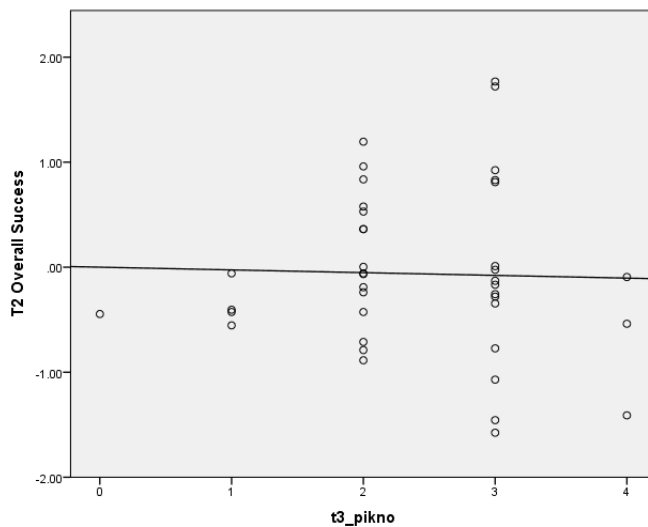


Figure 3.10. Scatter plot of T2 PI Knowledge and T2 Overall Success for all participants with regression line.

A big question regarding the results is why the participants in both training groups increased the number of employees, but not their sales. One possible explanation is that participants focused on changing and improving their business rather than on selling (especially in the action-based training where there was a significant increase in overall PI), resulting in a short-term reduction of sales. With the perspective of an improved business that is growing, it would then make sense to employ new people even with a temporary reduction of sales. Future research should focus on long-term results as well as on a process view of evaluation to support or contradict his interpretation with more measurement waves, thus scientists would be able to calculate a growth model for analyzing the effects of interventions and business changes. Another explanation might be that we made them overoptimistic through the training, expecting to get more sales in the future and thus increasing their number of employees. If this explanation holds true, a too high level of PI might be harmful as well, an aspect of PI that has not been researched well by now.

We found that the action-based training was able to significantly increase PI behavior compared to the knowledge-based training and the control group. This is an important result, as it shows that although the participants in the knowledge-based training had higher PI knowledge, they were unable to derive actions from their knowledge and the training had a large negative effect on PI behavior. Action theory offers a suitable explanation for this, because newly acquired behaviors compete with old routines and need to be practiced in order to successfully implement them (Frese & Zapf, 1994). In the action-based training, the participants had the opportunity to routinize newly acquired behaviors and as such show more PI behavior than in the knowledge-based training.

Next, we want to discuss our “lessons learned” throughout the field work in training business owners in developing countries to assist other research with their work. First of all, we were very surprised that some of the training participants refused to take further part in our study, arguing that they had already received the training and would not get anything out of their time for doing the interview and filling out the questionnaire. This is something we have not encountered before – maybe a useful strategy would be to give out the training certificates only after the study has ended, or to provide some extra monetary compensation or a lottery to ensure motivated participants.

Second, we might have encountered some problems with randomization. Due to our small sample size, we encountered the problem that our control group had significantly lower employees than both training groups. Analyzing this, we found out that the majority (65%) of the business owners in the control group had a business in the commerce sector, mostly arts & crafts, but also food and wholesale. In the action/knowledge training, only 8% / 53% had a business in the commerce sector. This helps to explain why the control group had fewer employees but higher sales, as in a sales business fewer employees are needed to generate higher sales than in a production business.

3.6.1 Strengths and Limitations

The biggest strength of the present study is that we compared the effects of two different training methods: an action-based and a knowledge-based trainings. Another strength of this study is that we used a pre-/posttest design that allows us to measure the real impact of the training programs controlling for maturation, dropout and so on. The biggest limitation of our study is the small sample size. Also, it would have been nice to use accounting data. However, in a developing country, many business owners don't do proper bookkeeping, thus there might be problems of memory distortion or social desirability. Nonetheless, we found a significant correlation of logarithm of sales and number of employees (T1 $r = .44$, $p < .01$, T2 $r = .33$, $p < .05$).

3.6.2 Future Research

Future research should include comparison not only to other training methods, but also to other theories taught with the same methodology, for example using an action-based training for teaching personal initiative as well as business skills like accounting or advertising. Another interesting methodology that will continue to gain importance because of the range of coverage and flexibility is the use of massive open online courses (MOOC), e.g. as described by Al-Atabi & DeBoer (2014). Also, research should focus on analyzing the working mechanisms of different training methodologies, including possible moderators like for example characteristics of trainers (which type of trainer is suited best for what methodology) and characteristics of participants (which type of participant benefits best from what methodology). Business ownership education could benefit from not only focusing on “hard” dependent business variables like number of employees or sales, especially the sales variable seems to be a bit unreliable in our study. Researchers thus should focus on other variables to measure business ownerial success, for example whether business owners pay

back a loan they received. Another interesting approach would be a mixed model: using a knowledge-based approach for fields in which knowledge is most important, and using an action-based approach for fields that rely on behavior.

3.6.3 Conclusion and Implications

Business ownership is an active concept. Our study shows that an action-based training approach is the best way to increase PI behavior among training participants, while knowledge is increased most through a knowledge-based training approach. Thus we conclude that entrepreneurship education needs special attention according to the results that shall be attained – for spreading knowledge about entrepreneurship, a lecture seems to be a good idea, but for developing students into active business owners, an action-based approach should be used.

CHAPTER 4

Conclusion and General Discussion

With this dissertation, I narrow the scientist-practitioner-gap in presenting a human resources approach to entrepreneurship regarding two main aspects: First, I show that selection instruments work for small business borrowers. Second, I show that personal initiative (PI) can be improved using an action-based and a knowledge-based treatment, and that both treatments have a positive effect on entrepreneurial success. The results have various implications for scientists as well as for practitioners.

The most important implication for scientists is the finding that a predictive model built on low-stakes data was not suitable for high-stakes predictions. The second important implication is that a predictive model built on high-stakes data worked quite well for high-stakes predictions. With a large sample (N=37,489), we were able to show that personality variables like conscientiousness and integrity of entrepreneurs help to predict loan default. Thus, the used test battery for personality and integrity seems to be a valid utility for selection even though the tests themselves might be prone to faking – or, at least, produced different answers in a high-stakes than in a low-stakes context. In analyzing the differences between low- and high-stakes settings, we followed a call by Stark et al. (2001). We additionally employed an alternative approach to examining faking via curve distributions. Future research should try to reproduce these findings in other countries and also using other selection instruments like situational judgement tests (not only regarding investments – for example when small business owners want to employ somebody), and so on.

Our results suggest that scientists should focus more on underlying processes (like König et al. (2007) with their “ability to identify criteria”) that account for differences between low- and high-stakes situations instead of hunting for non-fakeable instruments or

lying scales that identify fakers. Practitioners should use caution when choosing selection instruments: have they been validated in a high-stakes context? In addition, practitioners should not be too worried about faking (and maybe as a consequence make the mistake of not using a scientific selection instrument) as long as the instrument has been validated in a high-stakes context.

Another important finding of this dissertation is that we not only were able to identify and assess the characteristics that are responsible for repaying loans, but that we were also successful in improving necessary skills (i.e. personal initiative) for entrepreneurial success using different treatment methods. In chapter three, we show how the scientific theory of PI can be adapted into an educational treatment. We followed a call by McKenzie & Woodruff (2013) for studies testing different treatments for educating entrepreneurs in using an action-based and a knowledge-based treatment for teaching PI. We were able to show that an action-based training approach works best for PI behavior, while a knowledge-based training approach works best for imparting knowledge. With a sample group of $N = 47$, we were able to show that both treatments lead to an increase in the overall success of the participants.

Scientists should use these results for further analyzing the necessary skills / human capital and the variables that make an entrepreneur successful under certain conditions, for example scarce resources. This question is of special importance for further entrepreneurship education, e.g. when thinking of online learning – is it enough for an entrepreneur to have knowledge on successful entrepreneurship, or is it important that s/he is trained to show a desired behavior? We call for scientists to focus on different teaching methods in order to answer this question. Practitioners should keep in mind that if they are aiming at changing behavior, they should try an action-based approach instead of a mere lecture.

Next, we want to discuss the lessons learned of this dissertation. Regarding the use of selection instruments for small businesses borrowers in chapter two, we were able to present a

study based on a large international sample that promises a high generalizability. Using a computer-based test, we were able to eliminate problems with data assessment and to generate a large sample at relatively low costs. We suggest to other researchers to use equivalent assessing methods whenever possible. It also seems reasonable to pay more attention to the different characteristics of low- and high-stakes situations as well as variable distributions.

For the training approach presented in chapter three, we encountered a number of problems we want to share. First, the small sample size is the main issue of the presented study. Therefore, future research should focus on train-the-trainer-approaches and other possibilities like online learning in order to have multipliers for generating larger sample sizes. Second, we had an unusual large drop of participants in our study. We suggest that researchers should oblige training participants to keep contact themselves in order to receive a training certificate, or maybe using a small deposit to increase the interest of participants to stay in the study until the very end. Third, a study by de Mel, McKenzie, & Woodruff (2009) suggests that asking entrepreneurs for their profit provides a more accurate measure than asking detailed questions on sales like we did with our study. Since we had some questionable results regarding the sales variable (both training groups increased the number of their employees while their absolute sales level decreased), using profits instead might offer a solution to this issue. We also encountered some technical problems with organizing interview files on local hard drives. Hence, we suggest the use of online assessment to make sure that data are not overwritten by accident. This can be realized for interviews as well, when the interviewer uses online assessment tools and directly types in the answers of the interviewee instead of saving documents manually.

With our study, we were unable to reproduce findings of Glaub et al. (2014) regarding a mediating effect of PI for training participation on success. This can mainly be explained through the small sample size of our study, thus future research should try to reproduce the

findings of Glaub et al. with larger sample sizes and also different methodologies like a knowledge-based training. Finding different (or the same!) mediator variables for an action- vs. a knowledge-based training would help to explain the process of entrepreneurial education and give practitioners detailed ideas on what treatments to utilize.

Altogether, this dissertation addresses practical issues in entrepreneurship through providing a human resources approach. We believe that it is crucial to narrow the scientist-practitioner gap through presenting and publishing studies with a direct practical background. Entrepreneurship is an important research field as it offers a solution for issues of job creation, wealth, and innovation. In helping to strengthen the small business sector, we can fight poverty and increase economic growth.

References

- Ahiarah, S. (1989). "Strategic Management and Business ownership Courses at Undergraduate Level: Can One Inform the Other?" *Proceedings of the 1989 Small Business Institute Director's Association*, 60–66.
- Al-Atabi, M., & DeBoer, J. (2014). Teaching entrepreneurship using massive open online course (MOOC). *Technovation*, 34(4), 261-264.
- Alliger, G. M., & Dwight, S. A. (2000). A meta-analytic investigation of the susceptibility of Integrity tests to faking and coaching. *Educational and Psychological Measurement*, 60(1), 59-72.
- Anderson, R. (2007). *The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation*. Oxford University Press.
- Ash, P. (1970). Validation of an instrument to predict the likelihood of employee theft. *Proceedings of the 78th Annual Convention of the American Psychological Association*, 579-580.
- Ash, P. (1971). Screening employment applicants for attitudes toward theft. *Journal of Applied Psychology*, 55, 161 -164.
- Autio, E. (2005). *Global Entrepreneurship Monitor 2005 Report on High-Expectation Entrepreneurship*. London: London Business School.
- Bae, T. J., Qian, S., Miao, C., & Fiet, J. O. (2014). The Relationship Between Entrepreneurship Education and Entrepreneurial Intentions: A Meta-Analytic Review. *Entrepreneurship Theory and Practice*, 38(2), 217-254.
- Baldwin, T. T., & Ford, J. K. (1988). Transfer of training: A review and directions for future research. *Personnel Psychology*, 41, 63-105.
- Barr, S. H., Baker, T. E. D., Markham, S. K., & Kingon, A. I. (2009). Bridging the valley of death: Lessons learned from 14 years of commercialization of technology education. *Academy of Management Learning & Education*, 8(3), 370-388.
- Barrick, M., & Mount, M. (1991). The Big Five personality dimensions and job performance: a meta-analysis. *Personnel Psychology*, 44, 1–26.
- Baum, J. R., Frese, M., & Baron, R. A. (Eds.). (2014). *The psychology of entrepreneurship*. Psychology Press.
- Birch, D. L. (1987). *Job creation in America*. New York: Free Press.
- Birkeland, S. A., Manson, T. M., Kisamore, J. L., Brannick, M. T., & Smith, M. A. (2006). A Meta-Analytic Investigation of Job Applicant Faking on Personality Measures. *International Journal of Selection and Assessment*, 14(4), 317-335.
- Bozdogan, H. (1987). Model selection and Akaike's information criterion (AIC): The general theory and its analytical extensions. *Psychometrika*, 52(3), 345-370.
- Brandstaetter, V., Heimbeck, D., Malzacher, J. T., & Frese, M. (2003). Goals need implementation intentions: The model of action phases tested in the applied setting of continuing education. *European Journal of Work and Organizational Psychology*, 12(1), 37-59.
- Bulmer, M. G. (1979). *Principles of Statistics*. Dover.
- Christiansen, N. D., Goffin, R. D., Johnston, N. G., & Rothstein, M. G. (1994). Correcting the 16PF for faking: Effects on criterion-related validity and individual hiring decisions. *Personnel Psychology*, 47, 847–860.
- Cook, T. D., Campbell, D. T., & Peracchio, L. (1990). Quasi experimentation. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of Industrial and Organizational*

References

- Psychology* (2nd ed., Vol.1, pp. 491-576). Palo Alto, CA: Consulting Psychologists Press.
- Cramer, D. (1998). *Fundamental statistics for social research: Step-by-step calculations and computer techniques using SPSS for Windows*. Psychology Press.
- Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing*, 18(3), 301-331.
- de Mel, S., McKenzie, B., & Woodruff, C. (2014). Business training and female enterprise start-up, growth, and dynamics: Experimental evidence from Sri Lanka. *Journal of Development Economics*, 106, 199-210.
- de Mel, S., McKenzie, D. J., & Woodruff, C. (2009). Measuring microenterprise profits: Must we ask how the sausage is made?. *Journal of development Economics*, 88(1), 19-31.
- de Mel, S., McKenzie, D., & Woodruff, C. (2008). Returns to capital in microenterprises: Evidence from a field experiment. *Quarterly Journal of Economics*, 123, 1329-1372.
- Deltas, G. (2003). The small-sample bias of the Gini coefficient: results and implications for empirical research. *Review of economics and statistics*, 85(1), 226-234.
- Dilchert, S., Ones, D. S., Viswesvaran, C., & Deller, J. (2006). Response distortion in personality measurement: born to deceive, yet capable of providing valid self-assessments?. *Psychology Science*, 48(3), 209.
- Donovan, J. J., Dwight, S. A., & Hurtz, G. M. (2003). An assessment of the prevalence, severity, and verifiability of entry-level applicant faking using the randomized response technique. *Human Performance*, 16(1), 81-106.
- Donovan, J. J., Dwight, S. A., & Schneider, D. (2013). The impact of applicant faking on selection measures, hiring decisions, and employee performance. *Journal of Business and Psychology*, advance online publication. doi:10.1007/s10869-013-9318-5
- Drexler, A., Fischer, G., & Schoar, A. (2014). Keeping it simple: Financial literacy and rules of thumb. *American Economic Journal: Applied Economics*, 6(2), 1-31.
- Dwight, S. A., & Alliger, G. M. (1997). Using response latencies to identify overt integrity test dissimulation. In *13th Annual Conference of the Society for Industrial and Organizational Psychology*, St. Louis, MO.
- Ellingson, J. E., Sackett, P. R., & Hough, L. M. (1999). Social desirability corrections in personality measurement: Issues of applicant comparison and construct validity. *Journal of Applied Psychology*, 84(2), 155.
- Fernald, L. W., & Solomon, G. T. (1993). Assessing the need for small business management / entrepreneurship courses at the university level. 4. "Real Riches" to Girtown, 6, 29.
- Fiet, J. O. (2001a). The theoretical side of teaching entrepreneurship. *Journal of Business Venturing*, 16(1), 1-24.
- Fiet, J. O. (2001b). The pedagogical side of entrepreneurship theory. *Journal of business venturing*, 16(2), 101-117.
- Frese, M. (2009). *Toward a psychology of entrepreneurship: An action theory perspective*. Now Publishers Inc.
- Frese, M., Beime, S., & Schoenborn, S. (2003). Action training for charismatic leadership: Two evaluations of studies of a commercial training module on inspirational communication of a vision. *Personnel Psychology*, 56(3), 671-698.
- Frese, M., & Gielnik, M. M. (2014). The psychology of entrepreneurship. *Annual Review of Organizational Psychology and Organizational Behavior*, 1, 413-438.
- Frese, M., Kring, W., Soose, A., & Zempel, J. (1996). Personal initiative at work: Differences between East and West Germany. *Academy of Management journal*, 39(1), 37-63.
- Frese, M., & Zapf, D. (1994). Action as the core of work psychology: A German approach. In H. C. Triandis, M. D. Dunnette & L. M. Hough (Eds.), *Handbook of Industrial and*

References

- Organizational Psychology* (Vol. 4, pp. 271-340). Palo Alto, CA Consulting Psychologists Press.
- Ford, J. K., Kozlowski, S. W. J., Kraiger, K., Salas, E., & Teachout, M. S. (1997). *Improving training effectiveness in work organizations*. Mahwah, NJ: Lawrence Erlbaum.
- Gagne, R. M. (1984). Learning outcomes and their effects: Useful categories of human performance. *American Psychologist*, *39*(4), 377.
- Gielnik, M. M., Frese, M., Kahara-Kawuki, A., Katono, I. W., Kyejjusa, S., Ngoma, Munene, J., Namatovu-Dawa, R., Nansubuga, F., Orobia, L., Oyugi, J. Sejjaka, S., Sserwanga, A., Walter, T., Bischoff, K. M., & Dlugosch, T. J. (2015). Action and action-regulation in entrepreneurship: evaluating a student training for promoting entrepreneurship. *Academy of Management Learning & Education*, *14*(1), 69-94.
- Gilli, M. (2006). An application of extreme value theory for measuring financial risk. *Computational Economics*, *27*(2-3), 207-228.
- Glaub, M., Frese, M., Fischer, S., & Hoppe, M. (2014). Increasing personal initiative in small business managers or owners leads to entrepreneurial success: A theory-based controlled randomized field intervention for evidence-based management. *Academy of Management Learning & Education*, *13* (3), 954-979.
- Glaub, M., & Frese, M. (2011). A critical review of the effects of entrepreneurship training in developing countries. *Enterprise Development and Microfinance*, *22*(4), 335-353.
- Goldberg, N. (2005). *Measuring the Impact of Microfinance: Taking Stock of What We Know*. Grameen Foundation USA: Grameen Foundation USA Publication Series.
- Gollwitzer, P. M. (1999). Implementation intentions - Strong effects of simple plans. *American Psychologist*, *54*(7), 493-503.
- Gorman, G., Hanlon, D., & King, W. (1997). Some research perspectives on entrepreneurship education, enterprise education and education for small business management: a ten-year literature review. *International small business journal*, *15*(3), 56-77.
- Griffith, R. L., Chmielowski, T., & Yoshita, Y. (2007). Do applicants fake? An examination of the frequency of applicant faking behavior. *Personnel Review*, *36*(3), 341-355.
- Gumbel, E. J., & Lieblein, J. (1954). *Statistical theory of extreme values and some practical applications: a series of lectures* (Vol. 33). Washington: US Government Printing Office.
- Hayes, T. L. (2013). Review of: Matthias Ziegler, Carolyn MacCann, and Richard D. Roberts.(Eds.). *New Perspectives on Faking in Personality Assessment*. Oxford, UK: Cambridge University Press. *Personnel Psychology*, *66*(3), 798-801.
- Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology*, *67*, 451-470.
- Hogan, R. (1991). Personality and personality measurement. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology*, *2*, 873-919. Palo Alto, CA: Consulting Psychologists Press.
- Hogan, R., Hogan, J., & Roberts, B. W. (1996). Personality measurement and employment decisions. *American Psychologist*, *51*, 469 - 477
- Honig, B. (2004). Entrepreneurship Education: Toward a Model of Contingency-Based Business Planning. *Academy of Management Learning & Education*, *3*(3), 258-273.
- 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.
- Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological bulletin*, *96*(1), 72.

References

- Karlan, D., & Zimmman, J. (2009). *Expanding Microenterprise Credit Access: Using Randomized Supply Decisions to Estimate the Impacts in Manila*. New York City: The Financial Access Initiative and Innovations for Poverty Action.
- Klinger, B., Khwaja, A. I., & Del Carpio, C. (2013). *Enterprising Psychometrics and Poverty Reduction*. Springer.
- König, C. J., Klehe, U. C., Berchtold, M., & Kleinmann, M. (2010). Reasons for being selective when choosing personnel selection procedures. *International Journal of Selection and Assessment*, 18(1), 17-27.
- König, C. J., Melchers, K. G., Kleinmann, M., Richter, G. M., & Klehe, U. C. (2007). Candidates' ability to identify criteria in nontransparent selection procedures: Evidence from an assessment center and a structured interview. *International Journal of Selection and Assessment*, 15(3), 283-292.
- Kirkpatrick, D. L. (1959). Techniques for evaluating training programs. *Journal of the American Society of Training and Development*, 13, 3-9.
- Koop, S., De Reu, T., & Frese, M. (2000). Entrepreneurial orientation and personal initiative. In M. Frese (Ed.), *Success and failure of microbusiness owners in Africa: A psychological approach* (pp. 55 – 76). Greenwood Publishing.
- Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation. *Journal of applied psychology*, 78(2), 311.
- Krauss, S. I. (2003). Psychological success factors of small and micro business owners in Southern Africa: A longitudinal approach (Doctoral dissertation, Universitätsbibliothek Giessen).
- Kroger, R. O., & Turnbull, W. (1975). Invalidity of validity scales: The case of the MMPI. *Journal of Consulting and Clinical Psychology*, 43(1).
- Kunin, T. (1955). The construction of a new type of attitude measure. *Personnel Psychology*, 8, 65-78.
- Kuratko, D. F. (2003). Entrepreneurship education: Emerging trends and challenges for the 21st century. *Coleman Foundation White Paper Series for the United States Association of Small Business and Entrepreneurship* (pp. 1–39). Muncie, IN: Ball State University, College of Business, The Entrepreneurship Program.
- Levashina, J., Morgeson, F. P., & Campion, M. A. (2009). They don't do it often, but they do it well: Exploring the relationship between applicant mental abilities and faking. *International Journal of Selection and Assessment*, 17(3), 271-281.
- London House Press. (1980). *Personnel Selection Inventory manual*. Park Ridge, IL: Author.
- Martin, B. C., McNally, J. J., & Kay, M. J. (2013). Examining the formation of human capital in entrepreneurship: a meta-analysis of entrepreneurship education outcomes. *Journal of Business Venturing*, 28(2), 211-224
- Martinez, A. C., Levie, J., Kelley, D. J., Saemundsson, R. J., & Schott, T. (2010). *Global Entrepreneurship Monitor special report: a global perspective on entrepreneurship education and training*. Global Entrepreneurship Monitor, United States.
- Massey Jr, F. J. (1951). The Kolmogorov-Smirnov test for goodness of fit. *Journal of the American statistical Association*, 46(253), 68-78.
- Mays, F. E. (2004). *Credit scoring for risk managers: the handbook for lenders*. Thomson/South-Western.
- McClelland, D. C. (1967). *Achieving society*. Simon and Schuster.
- McGrath, R. E., Mitchell, M., Kim, B. H., & Hough, L. (2010). Evidence for response bias as a source of error variance in applied assessment. *Psychological Bulletin*, 136, 450-470.

References

- McKenzie, D., & Woodruff, C. (2013). What are we learning from business training and entrepreneurship evaluations around the developing world?. *The World Bank Research Observer*, lkt007.
- McMullan, E., Chrisman, J. J., & Vesper, K. (2001). Some problems in using subjective measures of effectiveness to evaluate entrepreneurial assistance programs. *Entrepreneurship Theory and Practice*, 26(1), 37-54.
- McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management Review*, 31(1), 131-152.
- Mead, D. C., & Liedholm, C. (1998). The dynamics of micro and small enterprises in developing countries. *World Development*, 26(1), 61-74.
- Mester, L. (1997). What's the point of credit scoring? *Federal Reserve Bank of Philadelphia's Business Review (September/October)*, 3-16.
- Mezulis, A. H., Abramson, L. Y., Hyde, J. S., & Hankin, B. L. (2004). Is there a universal positivity bias in attributions? A meta-analytic review of individual, developmental, and cultural differences in the self-serving attributional bias. *Psychological Bulletin*, 130, 711-747.
- Miller, M., & Rojas, D. (2004). Improving access to credit for SMEs: An empirical analysis of the viability of pooled data SME credit scoring models in Brazil, Colombia & Mexico. *World Bank working paper*.
- Oosterbeek, H., Van Praag, M., & Ijsselstein, A. (2010). The impact of entrepreneurship education on entrepreneurship skills and motivation. *European economic review*, 54(3), 442-454.
- Ones, D. S., Viswesvaran, C., & Reiss, A. D. (1996). Role of social desirability in personality testing for personnel selection: the red herring. *Journal of Applied Psychology*, 81(6), 660.
- Ones, D. S., Viswesvaran, C., & Schmidt, F. L. (1993). Comprehensive meta-analysis of integrity test validities: Findings and implications for personnel selection and theories of job performance. *Journal of Applied Psychology Monograph*, 78, 679-703.
- Paulhus, D. L. (1984). Two-component models of socially desirable responding. *Journal of personality and social psychology*, 46(3), 598.
- Peeters, C. F., Lensvelt-Mulders, G. J., & Lasthuizen, K. (2010). A note on a simple and practical randomized response framework for eliciting sensitive dichotomous and quantitative information. *Sociological Methods & Research*, 39(2), 283-296.
- Peterson, M. H., Griffith, R. L., Converse, P. D., & Gammon, A. R. (2011). Using within-subjects designs to detect applicant faking. In *26th Annual Conference for the Society for Industrial/Organizational Psychology*, Chicago, IL.
- Prahalad, C. K. (2004). *Fortune at the bottom of the pyramid: Eradicating poverty through profits*. Upper Saddle River, NJ: Prentice Hall.
- 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.
- Raabe, B., Frese, M., & Beehr, T. A. (2007). Action regulation theory and career self-management. *Journal of Vocational Behavior*, 70(2), 297-311.
- Rasmussen, E. A., & Sørheim, R. (2006). Action-based entrepreneurship education. *Technovation*, 26(2), 185-194.
- 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.

References

- Reynolds, P., Bosma, N., Autio, E., Hunt, S., De Bono, N., Servais, I., Lopez-Garcia, P., & Chin, N. (2005). Global entrepreneurship monitor: Data collection design and implementation 1998–2003. *Small business economics*, 24(3), 205-231.
- Rideout, E. C., & Gray, D. O. (2013). Does entrepreneurship education really work? A review and methodological critique of the empirical literature on the effects of university-based entrepreneurship education. *Journal of Small Business Management*, 51(3), 329-351.
- Rosenbusch, N., Brinckmann, J., & Mueller, V. (2013). Does acquiring venture capital pay off for the funded firms? A meta-analysis on the relationship between venture capital investment and funded firm financial performance. *Journal of Business Venturing*, 28, 335-353.
- Rosse, J. G., Stecher, M. D., Miller, J. L., & Levin, R. A. (1998). The impact of response distortion on preemployment personality testing and hiring decisions. *Journal of Applied Psychology*, 83(4), 634.
- Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass*, 5(6), 359-371.
- Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle* (Vol. 55). Transaction publishers.
- Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Journal*, 25, 217-226.
- Shantz, A., & Latham, G. (2011). The effect of primed goals on employee performance: Implications for human resource management. *Human Resource Management*, 50, 289-299.
- Smith, B., & Robie, C. (2004). The Implications of Impression Management for Personality Research in Organizations. In B. Schneider & D. Smith (Eds.), *Personality and Organizations* (pp. 111 – 138). Mahwah: Lawrence Erlbaum Associates.
- Stajkovic, A. D., Locke, E. A., & Blair, E. S. (2006). A first examination of the relationships between primed subconscious goals, assigned conscious goals, and task performance. *Journal of Applied Psychology*, 91, 1172-1180.
- Stark, S., Chernyshenko, O. S., Chan, K. Y., Lee, W. C., & Drasgow, F. (2001). Effects of the testing situation on item responding: Cause for concern. *Journal of Applied Psychology*, 86(5), 943.
- Stewart, G. L., & Carson, K. P. (1995). Personality dimensions and domains of service performance: A field investigation. *Journal of Business and Psychology*, 9(4), 365–378.
- The World Bank (2010). *Doing Business 2011: Making a Difference for Entrepreneurs*. Annual report
- Thomas, L. C., Edelman, D. B., & Crook, J. N. (2002). *Credit scoring and its applications*. Siam.
- Unger, J. M., Rauch, A., Frese, M., & Rosenbusch, N. (2011). Human capital and entrepreneurial success: A meta-analytical review. *Journal of Business Venturing*, 26(3), 341-358.
- Utsch, A., & Rauch, A. (2000). Innovativeness and initiative as mediators between achievement orientation and venture performance. *European journal of work and organizational psychology*, 9(1), 45-62.
- Van Iddekinge, C. H., Roth, P. L., Raymark, P. H., & Odle-Dusseau, H. N. (2012). The criterion-related validity of Integrity tests: An updated meta-analysis. *Journal of Applied Psychology*, 97(3), 499.

References

- Walter, T., Rosa, P., Barabas, S., Balunywa, W., Sserwanga, A., Namatovu, R., et al. (2005). *Uganda 2004 GEM Report*. Kampala: Makerere University Business School.
- Yunus, M. (1999). The Grameen Bank. *Scientific American*, 281(5), 114-119.
- Zhao, H., Seibert, S. E., & Lumpkin, G. T. (2010). The Relationship of Personality to Entrepreneurial Intentions and Performance: A Meta-Analytic Review. *Journal of Management*, 36(2), 381-404.
- Ziegler, M., MacCann, C., & Roberts, R. (Eds.). (2011). *New perspectives on faking in personality assessment*. Oxford University Press

Appendix

A. Measurement Instrument

PI Knowledge

Glaub, M., Frese, M., Fischer, S., & Hoppe, M. (2014). Increasing personal initiative in small business managers or owners leads to entrepreneurial success: A theory-based controlled randomized field intervention for evidence-based management. *Academy of Management Learning & Education*, 13 (3), 954-979.

Instructions

You will now find situations of small-business owners. Always think about how somebody would act in the described situation if she/he showed personal initiative. Please tick the answer which you think is correct. Only one statement is correct.

Example: Here a person has answered that the goal „decreasing the expenses in the next month“ would be the best goal.

(X) „decreasing the expenses in the next month“

1. Mr H. wants to set a goal for his business. If he showed personal initiative: which goal would he set?

() introduce a new product competitors don't sell

() copy the product range of the competitors

() keep the product range the same

() reduce the product range

2. Mr C. wants to set goals for his business and thinks about the time range. If he showed personal initiative: what would he do?

() set goals with a time range up to maximum 3 weeks

() set goals with a time range up to maximum 3 months

() set goals with a time range up to maximum one year

() set goals with a time range up to two years

Appendix

3. Mr. C wants to increase his profit by 20 percent within the next year. After two months he notices that this is not as easy as he thought. If he showed personal initiative: what would he do?

- give up the goal
- keep the goal
- change the goal to 10 percent increase
- change the goal to 5 percent increase

4. Mrs. K. sells clothes. Considering designs, what would she do if she showed personal initiative?

- Not try to find out anything about fashion.
- Try to find out the actual fashion and what the fashion will be in the next year.
- Only find out what the actual fashion is.
- Remember what the fashion was last year.

Interview

self-developed

How old are you?

Years

Gender

Male

Female

Are you married?

Yes

No

How many children do you have?

Number

How many of your relatives own a business?

Any of parents

Any of brothers / sisters

Any of grandparents

Any of aunts / uncles

F Are you currently the owner of a business?

(If more than one, all following questions refer to the most successful one)

No

Yes

Can you please describe the main product or service that you offer?

Within the last twelve months, have you introduced any changes (e.g. new or more advertising, new products or services, new branches etc.) in your work/business? (Think of the biggest problems you have had within the last twelve months.) Why did you introduce them (was it necessary / how did you react)? Who told you to do so / where did you get the idea? Did your competitors do the same?

Within the next twelve months, are you planning to introduce any changes (e.g. new or more advertising, new products or services, new branches etc.) in your work/business? Why and how do you want to introduce them (is it necessary to do so)? Who told you to do so / where did you get the idea? Do you think your competitors will do the same?

Rating: Personal Initiative (self-starting, proactive, persistent)
make a rating per reported behavior / planning / opportunity of:

- Quantitative initiative: how much energy went into the activity / will be necessary? 0 for a too abstract behavior description (e.g. “get more customers”), 1 for a rough description and 2 for a detailed description of the participants’ behavior
- Qualitative initiative: how self-starting, proactive, persistent is the activity? 5 point scale with 1 (very little) – 5 (very much)

In the last year, what was the sales level in a good month, in a bad month, and in a fair month?

Good	USh
Bad	USh
fair	USh

In the last year, how many good months, how many bad months, and how many fair months did you have?

Number of months

Good	
Bad	
Fair	

How many full-time employees do you have?
How many part-time employees do you have?