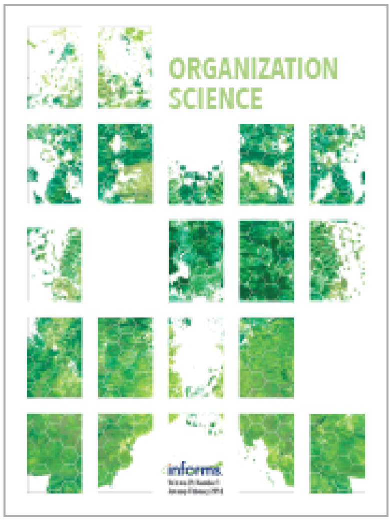

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Early-Stage Venture Incubation and Mentoring Promote Learning, Scaling, and Profitability Among Disadvantaged Entrepreneurs

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Abstract. Socially and educationally disadvantaged entrepreneurs often lack the knowledge and prior experience to develop and scale their businesses. Owing to limited educational and employment opportunities, poverty, and discrimination, these entrepreneurs frequently experience low business growth and performance. What factors influence the effectiveness of early-stage venture incubation and mentoring for promoting learning, scaling, and profitability among these entrepreneurs? Two studies in a business incubator serving low-income, underprivileged entrepreneurs in South Africa evaluate this question. Study 1 uses a matched, two-period case-control design to investigate the effects of incubation on business growth by comparing selected and incubated companies to similar also-selected but not incubated ones. The findings show that incubated companies grew 22% more in revenue and 15% more in employment than not incubated companies over the six months between applying to and graduating from the incubator. Study 2 uses instrumental-variable models to evaluate the role that mentoring played in improving business performance by analyzing data from seven cohorts of participants in the incubator randomly assigned to mentors. The findings show that participants assigned to high-ability (versus low-ability) mentors had 3.2% higher revenue and 3.5% higher profits one year after incubation. Further, the benefits of being mentored were more significant for businesses whose entrepreneurs had less pre-entry knowledge and experience, suggesting that mentoring supplemented gaps in human capital. These findings have implications for ways to support disadvantaged entrepreneurs and their businesses through mentoring and early-stage venture incubation.

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Keywords: entrepreneurship • incubators • entrepreneurial learning • mentoring • firm performance

Introduction

Recent research aimed at helping socially and educationally disadvantaged entrepreneurs develop their businesses has focused on tried-and-true solutions such as training and providing cash grants (Fiala 2013, de Mel et al. 2016, Anderson et al. 2018). These solutions, while potentially valuable for overcoming resource limitations to learning and experimentation, often overlook the additional support that entrepreneurs may need to develop their businesses. Entrepreneurship scholars have, therefore, sought to understand and quantify the role that incubators and accelerators play in facilitating entrepreneurial learning and new venture development (Petrou et al. 2010, Akçomak 2011, Cohen et al. 2019a). Through a combination of funding, peer support, and feedback from mentors, incubators catalyze entrepreneurial resource mobilization and serve as windows into early-stage venture development (Clough et al. 2019). Other conduits for learning, such as online courses, do not adequately address all the learning impediments at these stages, such as bounded rationality and limited resources to experiment, which make new business development particularly challenging (Cohen et al. 2019a).

While most of the existing studies of incubators and accelerators have focused on well-educated entrepreneurs, incubation and mentoring could be especially beneficial for socially and educationally disadvantaged entrepreneurs. In addition to being prone to the same challenges of bounded rationality and limited resources to experiment, disadvantaged entrepreneurs often face additional impediments to business growth and scaling, such as limited educational and employment opportunities to develop pre-entry knowledge and managerial experience (Anderson and Miller 2003, Baptista et al. 2014, McKenzie and Woodruff 2016). As a result, their businesses tend to remain small over time and fail at higher rates (Dencker et al. 2009, McKenzie and Woodruff 2016). Early-stage venture incubation and mentoring could address these challenges by providing a combination of funding and mentoring to support entrepreneurial learning, startup scaling, and profitability. This paper, therefore, aims to answer the following question: What factors influence the effectiveness of early-stage venture incubation and mentoring for promoting learning, scaling, and profitability among disadvantaged entrepreneurs?

Two studies in an incubator serving low-income, socially and educationally disadvantaged entrepreneurs from Soweto, South Africa, evaluated this question. The first study assessed the benefits of business incubation for selected and incubated businesses by comparing their growth over time to similar also-selected but not incubated ones (Study 1). The second study analyzed data from seven cohorts of entrepreneurs who were assigned at random to mentors of varying ability during incubation to identify the role that mentoring played in developing entrepreneurs' knowledge and improving their business performance (Study 2).

The findings showed that incubating their businesses and receiving mentoring helped disadvantaged entrepreneurs learn new knowledge, improved their business scaling (revenue and employment growth), and increased their profitability. Incubated businesses grew 22% more in revenue and 15% more in employment over six months than similar also-selected but not incubated businesses, with the same growth in operating costs. Also, entrepreneurs assigned to more capable mentors learned more new knowledge during their time in the incubator and experienced more significant business performance improvements after incubation. Entrepreneurs assigned to high-ability (versus low-ability) mentors experienced 3.2% higher revenue and 3.5% higher profits one year after completing the incubation program. Further, mentoring was more beneficial for entrepreneurs with less pre-entry knowledge and experience coming into the incubator, suggesting that mentoring supplemented gaps in formal education and experience.

These findings contribute to three areas of research. First, they contribute to the emerging literature on the benefits of incubators and accelerators for entrepreneurial learning (Hallen et al. 2014, Yu 2015, Lasrado et al. 2016). The findings suggest that incubation helps disadvantaged entrepreneurs learn and apply new knowledge by pairing these entrepreneurs with expert mentors. Second, this study demonstrates that in addition to in-class training, cash grants, and consulting (McKenzie and Woodruff 2016, Anderson et al. 2018, Bruhn et al. 2018), providing personalized mentoring contributes to lasting business performance improvements. These findings show that mentoring catalyzes entrepreneurial learning among disadvantaged entrepreneurs and thereby increases these entrepreneurs' capacity to found and manage more successful businesses. Third, these findings contribute to the literature on human capital and entrepreneurial success (van der Sluis and van Praag 2007, Fairlie and Robb 2009, Unger et al. 2011). They show that incubators can develop aspects of human capital that predict successful entrepreneurship, such as managerial knowledge about startup operations and scaling through mentoring.

Thus, inequality in prior education and high-skilled employment opportunities that affect disadvantaged entrepreneurs need not limit these entrepreneurs' ability to grow and scale their businesses. Indeed, the findings suggest that mentoring may be the most beneficial for entrepreneurs with the most significant gaps in pre-entry knowledge and experience about startup management. Therefore, early-stage venture incubation and mentoring could provide critical support tools for disadvantaged entrepreneurs facing impediments to growth and scaling, such as minority founders (Marvel et al. 2016; Younkin and Kuppuswamy 2018, 2019).

Theory and Hypotheses

Prior research has studied the role of human capital in entrepreneurial success extensively. This literature typically defines human capital as entrepreneurs' previous education and work experience (Davidsson and Honig 2003, Unger et al. 2011, Marvel et al. 2016). Within this definition, many scholars have also included aspects of human capital that entrepreneurs can develop, such as knowledge and skills, and personal initiative (Anderson and Miller 2003, Dencker et al. 2009, Sambasivan 2010). This literature has found that human capital affects the types of entrepreneurship that individuals pursue, their economic benefits from entrepreneurship, and their chances of business success. High-human-capital individuals, for example, are more likely to engage in opportunity recognition (Anderson and Miller 2003), more likely to enter nascent entrepreneurship (Davidsson and Honig 2003), and more likely to develop high-growth companies (Eesley 2016) than low-human-capital individuals. Further, entrepreneurs with more pre-entry knowledge and experience engage in more entrepreneurial planning (Brinckmann and Kim 2015). They also have higher growth expectations (Manolova et al. 2007), factors typically associated with higher chances of business success.

Beyond the start-up phase, high-human-capital entrepreneurs are less likely to fail (Batjargal 2007) and more likely to grow their businesses over time (Sambasivan 2010). They are also more likely to adopt sound management practices and, thereby, to realize higher sales growth and profitability than low-human-capital entrepreneurs (McKenzie and Woodruff 2016). High-human-capital entrepreneurs also tend to develop broad social networks and use these networks for sourcing new business opportunities and accessing external financing (Anderson and Miller 2003, Mosey and Wright 2007, Seghers et al. 2012). They also create more radical innovations (Marvel and Lumpkin 2007) and develop higher-growth ventures than do low-human-capital entrepreneurs (Eesley 2016). In sum, human capital confers a myriad of benefits associated with higher business growth and performance over time. Indeed, in their meta-analysis of the results of 70 independent samples based on the past 30 years of research, Unger et al. (2011) concluded that there is a significant positive effect of human capital on entrepreneurial success.

Scholars and policymakers have, therefore, sought ways to fill human capital gaps among disadvantaged entrepreneurs, including low-income individuals, women, and ethnic minorities. The evidence suggests that these entrepreneurs face the most significant impediments to developing successful businesses (Johnson et al. 2018, Younkin and Kuppuswamy 2018, Guzman and Kacperczyk 2019). Some aspects of human capital, particularly knowledge and skills, lend themselves to being developed through various interventions. For instance, in-class training (Field et al. 2010, McKenzie and Puerto 2017, Anderson et al. 2018) and external management consulting (e.g., Bloom et al. 2010; Bloom et al. 2013a, 2013b) can hone entrepreneurs' knowledge and skills.

Prior studies have shown that management consulting can improve business practices and thereby increase revenue, profitability, and total factor productivity (Bruhn et al. 2010; Bloom et al. 2013a, 2013b). Further, teaching management skills can confer significant and long-lived improvements in management practices, including recordkeeping, record analysis, and visits with customers (Karlan and Valdivia 2011, Higuchi et al. 2019). These changes can result in increased sales revenue and higher gross profit (Mano et al. 2012, Campos et al. 2017, Higuchi et al. 2019). This literature suggests that offering even basic training to cover book-based knowledge and providing free consulting can increase the chances of entrepreneurial success for disadvantaged individuals (McKenzie and Woodruff 2014, McKenzie and Puerto 2017).

Incubators and Their Benefits for Businesses Founded by Disadvantaged Entrepreneurs

Entrepreneurship scholars have noted the importance of incubators and accelerators for entrepreneurial learning (Cooper 1985, Argote and Fahrenkopf 2016, Clough et al. 2019). The existing literature, however, has focused primarily on well-educated, high-human-capital entrepreneurs (Hallen et al. 2014, Smith and Hannigan 2015, Cohen et al. 2019b). Thus, there is limited evidence about the benefits of incubators for businesses founded by socially and educationally disadvantaged entrepreneurs. Addressing these gaps is essential because the learning support that high-human-capital entrepreneurs need could differ substantially from the support that disadvantaged entrepreneurs may need to overcome impediments to business success (Lins and Lutz 2016, Younkin and Kuppuswamy 2018, Guzman and Kacperczyk 2019).

Further, the existing literature has produced mixed evidence about the benefits of incubators and accelerators for early-stage ventures, even for high-human-capital entrepreneurs in the United States. Some studies have found that accelerated businesses raise less money than similar not-accelerated businesses and close down earlier and more often (Yu 2015). Other studies have found that incubated businesses experience an immediate negative effect on their performance after incubation and face an increased likelihood of failure (Schwartz 2009). This research suggests that incubators and accelerators potentially expedite the time it takes for entrepreneurs to fail but do not help entrepreneurs grow their businesses in revenue and employment.

Existing studies of incubators and accelerators have also investigated the role that these organizations play in helping entrepreneurs overcome the problems related to learning, including bounded rationality (Cohen et al. 2019a, b). These studies have found that the benefits incubators and accelerators offer depend on entrepreneurs' backgrounds, including their prior knowledge, experience, and networks, and on the design elements of the programs, such as the frequency of feedback, the structure of cohort interactions, and the quality of mentors and advisers (Cohen et al. 2019b). Studies of university-run incubators (Lasrado et al. 2016) and participants in high-status accelerators in the United States (Hallen et al. 2014), for instance, have found that accelerated companies have higher rates of survival, generate more employment, and receive more funding. However, many potential mechanisms could contribute to these outcomes, including self-selection by high-human-capital entrepreneurs into university-run and high-status incubators and accelerators.

Prior research has suggested that businesses founded by disadvantaged entrepreneurs tend to grow less and fail at higher rates, in large part because their founders face significant gaps in their pre-entry knowledge and experience (Fiala 2013, McKenzie and Woodruff 2016). Thus, it is possible that the current research underestimates the benefits of incubators and accelerators for socially and educationally disadvantaged entrepreneurs. If business incubators support entrepreneurial learning (Ndabeni 2008, Dutt et al. 2016), then incubators could be potentially more valuable for growing businesses started by entrepreneurs who have less pre-entry knowledge and experience. Mentoring, for example, could help disadvantaged entrepreneurs diagnose problems with their business early, and thereby avoid costly mistakes. Incubators also offer much-needed kick-starter funding and networking opportunities, which socially and educationally disadvantaged entrepreneurs often lack.

These resources can supplement gaps in prior formal education and managerial experience for disadvantaged entrepreneurs that could hinder business growth. The resources that incubators provide could, therefore, be beneficial not only for entrepreneurial resource mobilization (Clough et al. 2019), but also for growing and scaling businesses founded by disadvantaged entrepreneurs. Incubators could enhance these entrepreneurs' ability to learn and improve their businesses through a combination of expert mentoring to overcome bounded rationality and fill gaps in pre-entry knowledge, kick-starter funding to enable business model testing and experimentation, and networking opportunities to find additional resources for growth and scaling. Incubators could thereby increase disadvantaged entrepreneurs' capacity to grow and scale their startup operations, leading to the following hypothesis:

Hypothesis 1. *Incubation will result in higher sales and employment growth for companies founded by disadvantaged entrepreneurs that underwent incubation, compared with similar also-selected but not incubated companies.*

Mentoring as a Tool to Support Disadvantaged Entrepreneurs' Learning and Performance

Mentoring, one type of resource that incubators provide, presents a potentially valuable tool for filling gaps in disadvantaged entrepreneurs' pre-entry knowledge and experience and thereby improving business performance (Clough et al. 2019; Cohen et al. 2019a, b). Both the availability and the quality of mentors that incubators provide to entrepreneurs in their cohorts could affect the value that entrepreneurs derive from the incubation process.

The literature on learning and knowledge transfer has found that individuals that serve as brokers and intermediaries—the mentors within incubators—are crucial for facilitating learning within organizations (Burt 1992, Reagans and McEvily 2003, Vedres and Stark 2010). These theories imply that mentors within incubators serve as repositories of knowledge and information that entrepreneurs can access. By being in structural positions to share diverse information and resources, mentors can provide valuable input to improve entrepreneurs' ability to absorb, process, and apply new knowledge (Argote and Miron-Spektor 2011, Argote and Fahrenkopf 2016, Cohen et al. 2019a). Mentors can, therefore, affect how much entrepreneurs learn by influencing both the types of knowledge they access and how they apply this knowledge.

Personalized mentoring could be especially helpful for socially and educationally disadvantaged entrepreneurs who may not have had the same sets of opportunities and choices available as more advantaged entrepreneurs (van der Sluis and van Praag 2007, Dencker et al. 2009, Pandey et al. 2017). By filling gaps in these entrepreneurs' formal education and work experience, mentoring can equalize the playing field among entrepreneurs from historically marginalized groups. It can help these entrepreneurs learn, absorb, and apply new knowledge to early-stage venture development and overcome common pitfalls to entrepreneurial success.

Mentoring can also help entrepreneurs apply new knowledge about operations and scaling for new ventures to their businesses to effectuate change and improve business performance. For example, mentors can advise entrepreneurs on how to hire and manage new employees, transition to serve mainstream customers, and grow demand for the venture's offering (Baron et al. 1996, 1999, 2001). Helping entrepreneurs navigate these critical stages of early-stage venture development and learn new approaches to solving problems at these stages can last for a lifetime and benefit the future ventures they found. Pairing entrepreneurs with more capable mentors during their time in an incubator could, therefore, provide them with higher-quality, more tailored advice to address their specific knowledge and experience gaps. Ultimately, mentoring can develop entrepreneurs' ability to improve, grow, and scale their businesses in ways that other solutions that also focus on learning, such as online courses, cannot, because of the tailored advice and personal attention that expert mentors provide.

The quality of mentoring that entrepreneurs receive during early-stage venture incubation could also affect how much new knowledge they learn and apply. Research on learning in higher education, for instance, has shown that advising has a positive relationship with student grades (Mu and Fosnacht 2019). Mentors who have proven themselves to be more effective could share better advice and strategies. As a result, the entrepreneurs they mentor could be better able to grasp essential ideas and apply that knowledge to improve their businesses. Capable mentors could provide entrepreneurs with the right guidance to overcome the setbacks that arise during the early stages of venture development. These mentors could, therefore, be more effective at improving entrepreneurs' learning during venture incubation than less capable mentors. These arguments lead to the following hypothesis about how mentors' ability affects entrepreneurs' learning during early-stage venture incubation:

Hypothesis 2a. *Pairing disadvantaged entrepreneurs with high-ability (versus low-ability) mentors during incubation will result in more considerable score improvements on tests of managerial knowledge.*

Furthermore, the quality of the mentoring that entrepreneurs receive during venture incubation could affect how well their businesses perform after they graduate. Entrepreneurs who have more capable mentors could be more effective at applying the knowledge they received during incubation to increase their ventures' long-term growth and viability. These entrepreneurs could thereby experience more substantial revenue and profitability growth for their businesses after graduating from the incubator. By these arguments, the quality of the mentors will be critical for improving entrepreneurs' post-incubator business performance through its effects on entrepreneurial learning, leading to the following hypothesis:

Hypothesis 2b. *Pairing disadvantaged entrepreneurs with high-ability (versus low-ability) mentors during incubation will result in more substantial revenue and profitability growth for their businesses through entrepreneurial learning.*

The Moderating Role of Entrepreneurs' Pre-entry Knowledge and Experience

Prior work has documented significant and persistent disparities among entrepreneurs in both human capital and business performance across income, ethnic, and gender divides (e.g., Field et al. 2010, Halkias et al. 2011, Thébaud 2015). The literature on human capital and entrepreneurship has found that more educated and experienced entrepreneurs are more likely to be capable managers and stewards of their fledgling organizations (van der Sluis and van Praag 2007, McKenzie and Woodruff 2016). They are, therefore, more likely to create organizations that survive and grow over time (Dimov and Shepherd 2005, Dimov 2010, McKenzie and Woodruff 2016).

The reasons for these disparities are that the channels through which entrepreneurs typically learn how to be more effective managers of their companies, including formal education and prior work experience, are highly unequally distributed across gender, ethnic, and income divides (e.g., Field et al. 2010, Halkias et al. 2011). Socially and educationally disadvantaged individuals often lack the knowledge and skills to develop their businesses owing to structural inequality and social discrimination (Bruhn and Zia 2013, McKenzie and Puerto 2017). These realities often translate into differences in aspirations and business performance. Studies have found, for example, that men's business growth expectations are higher than women's (Manolova et al. 2007). Further, the growth aspirations of opportunity-based entrepreneurs are also higher than those of necessity-based entrepreneurs, in large part because these typologies themselves capture inequalities in social status and family income (Baptista et al. 2014). Low-income minority entrepreneurs for instance, face more significant challenges with developing successful businesses than white, college-educated men (Younkin and Kuppuswamy 2018, 2019). These disparities in business performance arise, in no small extent, from rampant social discrimination (Marom et al. 2016; Younkin and Kuppuswamy 2018, 2019; Guzman and Kacperczyk 2019) and structural inequality that limits access to resources and business support from existing social networks (Anderson and Miller 2003).

The existing literature, therefore, suggests that the value of mentoring could be higher, the greater the disadvantages that the entrepreneurs face (Peters et al. 2004, Grimaldi and Grandi 2005, Cohen et al. 2019a). For instance, being mentored could be more beneficial for younger (versus older) entrepreneurs with less pre-entry knowledge and experience coming into an incubator, because these entrepreneurs have more significant gaps in their existing knowledge base and prior relevant work experience (van der Sluis and van Praag 2007, Dencker et al. 2009, Arlotto et al. 2011). For similar reasons, and owing to structural inequality, the benefits of mentoring could also depend on demographic characteristics affecting educational and employment opportunities, such as gender and ethnicity (Field et al. 2010, Halkias et al. 2011, de Mel et al. 2016).

Entrepreneurs' pre-entry knowledge and experience coming into an incubator could thus moderate the value of mentoring for learning during early-stage venture incubation. To the extent that mentoring supplements gaps in entrepreneurs' formal education and prior work experience, mentoring could be more valuable for socially and educationally disadvantaged entrepreneurs with less pre-entry knowledge about startup management and business scaling. By contrast, mentoring could be less helpful for entrepreneurs with more education and experience, for whom mentors could provide more redundant, and therefore potentially less useful, knowledge. These arguments imply that the benefits of personal mentoring will be lower for entrepreneurs with more pre-entry knowledge and experience coming into the incubator, leading to the following hypothesis:

Hypothesis 3. *The benefits of receiving personalized mentoring will decrease with entrepreneurs' pre-entry knowledge and experience.*

Data and Methods

Overview of Studies

Two studies tested the proposed hypotheses. Study 1 employed a matched case-control design using data from applicants to an early-stage venture incubator in South Africa. It investigated Hypothesis 1, whether incubated businesses experienced higher sales and employment growth over the same period compared with similar also-selected but not incubated ones. Study 2 tested Hypotheses 2 and 3, whether being paired with high-ability (versus low-ability) mentors in the incubator resulted in higher business revenue and profitability for entrepreneurs who participated in the incubator. This study used data from seven cohorts of participants in the incubator paired with expert mentors. These mentors varied in their track records and ability, observed from their work with prior participants. The design for this study used instrumental variable models to identify the causal effects of mentors' expertise on participants' business performance after incubation. These models provided estimates of the impact of mentoring on participants' score improvements on tests of managerial knowledge and subsequent business performance.

Setting

The setting for both studies was an early-stage venture incubator in South Africa founded to help promising entrepreneurs from Soweto and surrounding areas near Johannesburg develop high-growth businesses. The incubator serves socially and educationally disadvantaged entrepreneurs from low-income backgrounds. The incubator receives funding from a combination of government grants, equity providers, and donors supporting job creation and economic development in South Africa. Most applicants were attracted to the incubator because of the opportunity to learn the knowledge and skills necessary to grow and develop their businesses. The incubator uses both its website and word-of-mouth recommendations from prior participants to attract prospective applicants and advertises the resources available to participants widely. The selection of applicants into the incubator is competitive. The incubator's staff hand-pick a small number of applicants for each incoming cohort, after rigorous screening procedures. These procedures involve interviews and questionnaires asking applicants about the efforts they have undertaken to develop their businesses, and how they hope to benefit from the incubator.

The benefits of participating in this incubator, if selected, include receiving one-on-one mentoring in areas such as time management, operations, financial management, growth strategy, communication, human resources, business law, and capital sourcing. Additional benefits that the incubator offers to all participants include in-class training covering business topics such as accounting and bookkeeping and sales and marketing, and a small sum of kick-starter funding to support business development. The incubator's staff pair each entrepreneur with a mentor. These pairings last for the duration of the incubation program. During this time, mentors work individually with each entrepreneur to provide close guidance. The main variation in participants' experience comes from being paired with different mentors.

Study 1: Methods

Study 1 used a matched case-control two-period design using data from applicants to the incubator to evaluate whether incubated businesses performed better over time than similar also-selected but not incubated ones (Hypothesis 1). This study utilized data collected through mobile phone surveys distributed to applicants to this incubator to probe about their business performance at the time when they applied to the incubator and six months after they applied. The six months coincided with the end of the 24-week incubation program for selected and incubated applicants. This study aimed to compare the growth rates of similar businesses that were selected and incubated, relative to those that were also selected but not incubated.

Sample, Design, and Procedures

Study 1 used data from applicants to the incubator, collected anonymously end-to-end using mobile phone surveys with no individual identifying information collected about respondents. These surveys asked applicants about their business performance over time, both at the time of applying (T0) and six months after applying (T1). This method prevented the data from being individually identifiable to ensure accurate responses and confidentiality. Mobile phone surveys are recommended for hard-to-access populations (Firchow and Mac Ginty 2017, Vicente et al. 2018) and combine potentially higher response rates than using alternative landline methods, with the benefits of preserving respondent anonymity and confidentiality.

The sampling frame consisted of 2,153 individuals from the Johannesburg metropolitan area who had applied to the incubator over the past year, according to the incubator's records. Of this list 129 applicants could not be reached. From the remaining 2,024 applicants, 556 individuals returned completed surveys, for a response rate of 27.5%.[1] Of the 556 respondents, 347 respondents confirmed that they applied to the incubator within the past 12 months, a condition that was necessary to ensure comparability between the incubated and not incubated samples on performance metrics. From these respondents, 150 indicated that their businesses were selected. These respondents and their businesses comprised the primary data for the analyses. From these chosen applicants, 120 reported that their companies were incubated (treated group) and 30 said that their businesses were not incubated, despite having been selected (control group).

The treated and control groups had similar baseline (pre-treatment) performance in terms of their sales revenue, operating costs, employment, and business registration status at the time when they were selected to join the incubator (see Figure A1 of the Online Appendix). These comparisons suggest that these groups were plausible counterfactuals for each other when they were selected. Conditional on being selected, however, applicants were less likely to join the incubator the farther away from the incubator they lived, owing to the longer commuting distance.

The identification strategy, therefore, relied on adjusting the probability of being incubated (treated) conditional on being selected by using applicants' commuting distance to the incubator. Figure A2 and Table A2 in the Online Appendix show that the probability of being incubated decreased with applicants' commuting distance to the incubator. The analyses, therefore, estimated the effect of being incubated using the inverse-probability-weighted (IPW) average treatment effect (ATE) estimator. This estimator adjusts the ATE by the probability of being incubated (i.e., treated) as a weight in the estimation. This weight was estimated using a logistic link function predicting the likelihood that a selected applicant joined the incubator as a function of the residual of the applicant's commuting distance to the incubator (in squared kilometers) from the applicant's home address.[2] These residuals are the difference between the distance predicted from applicants' pre-treatment covariates and the observed commuting distance.[3]

Measures

The survey asked applicants about their monthly sales revenues, operating costs, and employee headcount, both at the time of applying to the incubator and six months after applying. The six-month period coincided with the 24-week incubation program for selected applicants that participated in the incubator. The survey questions prompted respondents to report their average, high, low, and typical sales revenue and business operating costs in Rand, and the total headcount of their employees, including both full-time and part-time employees. Respondents that participated in the incubator also reported how beneficial the program was for improving business performance.

Changes in Business Performance. Several measures assess the benefits of being incubated for changes in business performance. The first measure is the change in sales revenue for the businesses (in Rand), between the time of applying to the incubator (T0) and six months after applying (T1). The second measure is the change in monthly operating costs (in Rand) between the time of applying and six months after. The third measure is the change in employee headcount, including both paid full-time and part-time employees, using the same procedure. These measures looked at changes over time, by taking the ratio as $Log(1 + x_{t1}/x_{t0})$, where x_{t1} was the performance at T0, and x_{t0} was the performance at T1.[4]

Control Variables. Control variables included applicants' ethnicity (Black, Coloured, Asian/Indian), gender (male or female), and age. Furthermore, additional controls included the latitude and longitude coordinates of applicants' home addresses, to control for the effects of applicants' locations on their business operations.

Study 1: Results and Discussion

Descriptive Statistics

Table A1 of the Online Appendix provides descriptive statistics for the sample for Study 1. Figure A3 of the Online Appendix shows the composition of the sample, by industry, and by entrepreneurs' gender, age, and ethnicity. The average monthly sales revenue for selected applicants at the time of applying (T0) was about 9,378 Rand (about $637). The average monthly sales revenue six months after applying (T1) was about 14,013 Rand (about $953). The average operating costs at the time of applying were about 10,027 Rand per month (about $682). The average operating costs six months after applying were about 9,824 Rand per month (about $668). The average business profits at the time of applying were –649 Rand per month (a loss of about $44) and 4,189 Rand per month (a profit of about $285) six months later. The average employee headcount at the time of applying was 5.9 employees (with a standard deviation of 2.8 employees). The average employee headcount six months later was about 6.9 employees (with a standard deviation of 7.8 employees). The average commuting distance to the incubator for selected applicants was about 27 kilometers (761 km sq.), or about 16.7 miles. Compositionally, about 56% of applicants chosen in the sample were female. The average age for these applicants was 31.8 years, with a standard deviation of about seven years. Over 90% of applicants self-identified as Black South Africans, 6% as Coloured, and 3% as "Other." The primary ethnic groups (mother tongue) represented in the sample were Zulu (21%), Xhosa (14%), and Tswana (12%). The primary industries represented were Services (42.55%), Retail Sales (21.28%), and Manufacturing (9.57%).

Hypothesis Tests

As Table 1 shows, the treated group had higher sales and employment growth than the control group over the same period, between the time of applying (T0) and six months after applying (T1). In the case of treated applicants, T1 corresponds to the completion of the 24-week incubation program. The difference in the log sales revenue of these groups was 0.202 ($t = 2.23$, $p < 0.05$), which corresponds to 22.4% (= exp (0.202)-1) higher sales revenue for the treated group than the control group. The difference in log employee headcount was 0.144 ($t = 2.85$, $p < 0.01$), which corresponds to 15.5% higher employment growth for the treated group than the control group. There was no change in the costs or the rate of business registration (incorporation) between these groups. Both groups grew operating costs by 125% and increased their rate of registration by 61.6%.

Figure 1 plots the kernel density of the change in sales revenue and the change in total employee headcount across these groups. As this figure shows, more businesses achieved positive sales growth in the treated group than the control group. Further, more companies experienced positive employment growth in the treated group than the control group. Figure 2 plots the heterogeneity in the benefits of being incubated for companies founded by different types of entrepreneurs, looking at how the effects varied with entrepreneurs' age, ethnicity, and gender. As this figure shows, being incubated was most beneficial for young entrepreneurs, ages 18–24 and 30–35, compared with those over 35.

The benefits of being incubated were also more substantial for ethnic minority entrepreneurs (Swati and Sotho speakers). These ethnic groups represented about 7.6% and 2.5% of the population, respectively,

Table 1. Average Treatment Effect (ATE) of Being Incubated for Selected Applicants

	(1)	(2)	(3)	(4)
	Log(1 + *Sales T1*/*Sales T0*)	Log(1+ *Costs T1*/*Costs T0*)	Log(1+ *Employees T1*/*Employees T0*)	Log(1+ *Registered T1*/*Registered T0*)
	Difference in sales revenue	Difference in operating costs	Difference in employees	Difference in registration
ATE				
Hypothesis 1: Treated (incubated) compared with control	0.202*	0.109	0.144**	0.0290
	(2.23)	(1.30)	(2.85)	(0.80)
Potential outcomes mean				
Control (selected, but not incubated)	0.846***	0.754***	0.597***	0.616***
	(13.75)	(13.06)	(17.10)	(22.31)
IPW regressor				
Residual distance to incubator	0.0000346	0.0000156	0.0000677	0.0000313
	(0.47)	(0.20)	(0.81)	(0.31)
Intercept	0.0312	0.0334	−0.265	−0.0841
	(0.17)	(0.18)	(−1.11)	(−0.46)
N (treated)	120	120	120	120
N (control)	30	30	30	30

Notes. t statistics in parentheses. T0 denotes the time of applying. T1 means six months after applying, corresponding to the 24-week incubation period for selected applicants that joined the incubator. Inverse probability weighed (IPW) estimator using selected applicants' distance to the incubator (in kilometers) as a predictor of the probability of joining the incubator conditional on being selected. *Residual distance to incubator* is the residual of the geodesic distance on an ellipsoid (in squared kilometers) from each applicant's home address latitude and longitude coordinates to the incubator's address coordinates, after predicting this distance from the following pretreatment covariates: gender, age, ethnicity, business revenue at the time of applying, business operating costs at the time of applying, employees at the time of applying, and registration status at the time of applying.

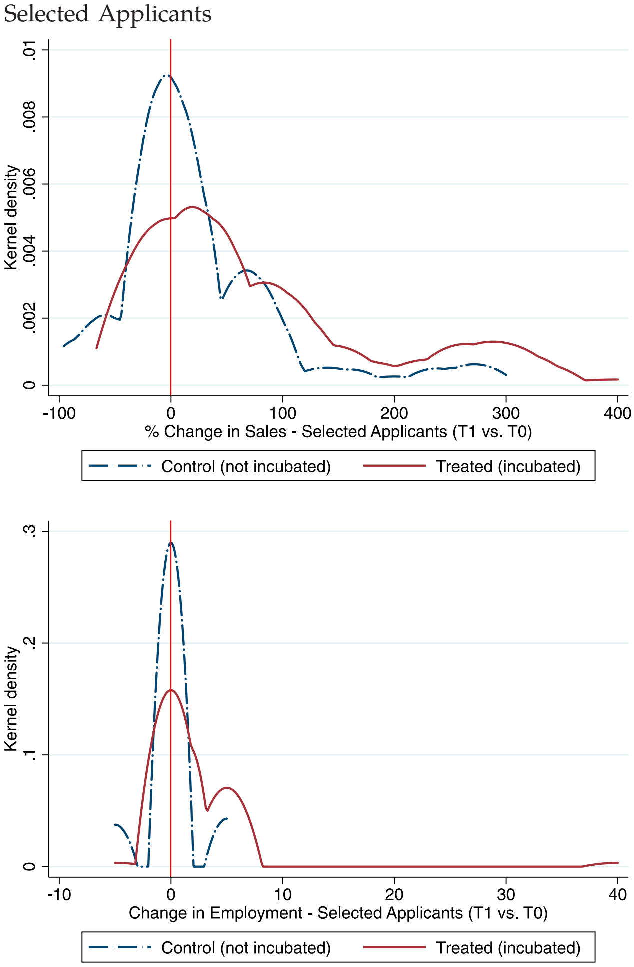
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests).

according to the 2011 South African national census. By contrast, the benefits were smallest for Zulu entrepreneurs, who represent the largest ethnic group in South Africa at 22.7% of the population. The benefits were roughly equivalent across genders, with both male and female entrepreneurs benefitting equally from business incubation. Finally, the benefits were more considerable for entrepreneurs who self-identified as an ethnic minority group, representing about 8.8% of the population in South Africa.[5]

Study 2: Methods

Study 2 used proprietary operating information from the incubator about participants over seven cohorts in the incubator to investigate the benefits of mentoring for entrepreneurs' learning (Hypothesis 2a) and subsequent business performance (Hypothesis 2b). This study further investigated whether mentoring was more beneficial for entrepreneurs with lower human capital and with characteristics affecting their pre-entry knowledge and experience (Hypothesis 3). This study used a central feature of this setting, that the incubator's staff assigned mentors to participants at random, independent of participants' and their businesses' characteristics. This feature enabled the identification of how mentoring affected changes in participants' knowledge during incubation, and business performance after incubation. Participants' mentor assignment served as an instrument for participants' learning during incubation. Further, data from the incubator about participants' attendance records and baseline exam scores provided controls for the effects of motivation to learn and prior knowledge at the time of entering the incubator.

Figure 1. (Color online) Treatment Effects of Incubation for Selected Applicants



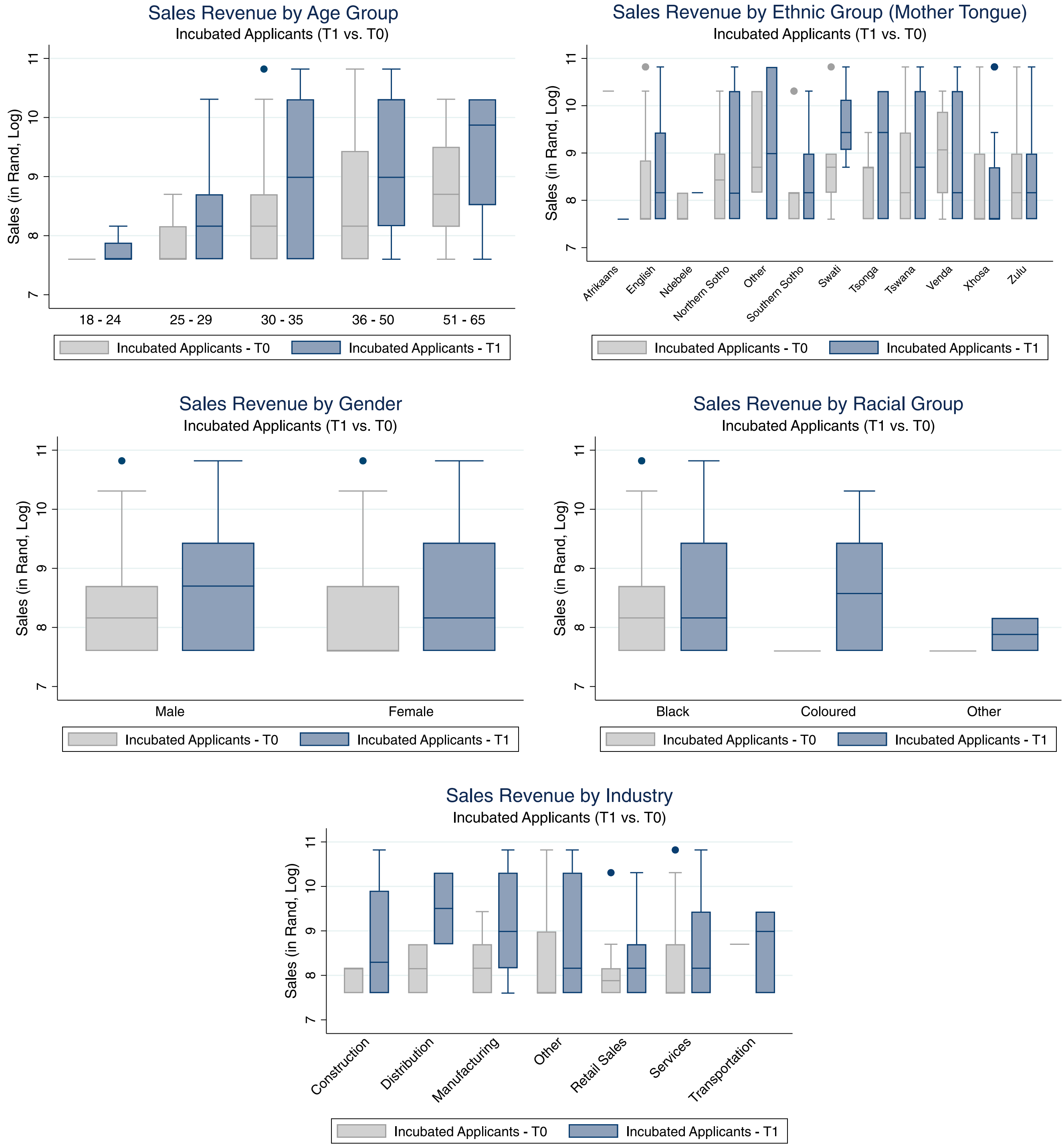
Sample, Design, and Procedures

The second set of analyses used two-stage least-squares instrumental variable (2SLS IV) regression models to estimate the effect of learning during incubation on post-incubation business performance. The reason for using 2SLS IV models was unobserved heterogeneity that could have endogenously affected both entrepreneurial learning and business performance after incubation. To deal with this endogeneity, the 2SLS IV models used entrepreneurs' random assignment to mentors over seven cohorts in the incubator as an instrument for entrepreneurial learning. Mentors with more robust track records of improving their mentees' performance were plausibly more effective at filling gaps in participants' pre-entry knowledge and experience. Entrepreneurs assigned to these high-ability mentors could have, therefore, learned more during their time in the incubator and improved their business performance by more than participants with less capable mentors.

Participants' mentor assignment meets the three conditions needed for identification. First, because the mentor assignment was random, whether a participant received a high-ability or low-ability mentor was independent of a participant's ability and business characteristics. Second, mentors' ability plausibly affected how much participants learned during the incubation program (instrument validity). Third, mentors were not involved with business operations or decisions once participants graduated from the incubator. Thus, participants' mentors could not have directly affected business performance after incubation except through participants' learning (exclusion restriction). The combination of these conditions enables identification of the effect of pairing participants with high-ability (versus low-ability) mentors on their learning and subsequent performance.

The analyses estimated the effects of mentor assignment on participants' learning and performance using operating data from the incubator. These data included mentors' track records of working with mentees from previous cohorts. This information came from the score improvements of past mentees, comprising the average difference between the baseline

Figure 2. (Color online) Heterogeneity in Treatment Effects of Incubation



and exit exam scores of these mentees on tests of core knowledge and skills required for business scaling. To account for both participant and company-specific heterogeneity, the models controlled for entrepreneurs' age, gender, ethnicity, and nationality, baseline exam scores (pre-entry knowledge), program dropout status, and operating costs (a proxy for firm size). The models also controlled for differences in participants' motivation and the peer effects within their cohorts during incubation.

The 2SLS IV models estimated each participant's business performance improvements after incubation using their mentor's track record as an instrument for learning during the incubation period. These models took the following functional form at the first and second stages of the estimation, where the first-stage models predicted entrepreneurial learning during incubation as a function of mentor ability, and the second-stage models predicted business performance after incubation as a function of entrepreneurial learning.

$$\text{First-stage: } Z_{1i} = \alpha_1 + \beta_1 \mathrm{IV}_i + \mathbf{X}_i'\beta + \varepsilon_{1i}$$
$$\text{Second-stage: } Y_i = \alpha_2 + \beta_2 \hat{Z}_{1i} + \mathbf{X}_i'\beta + \varepsilon_{2i}$$

In these models, Z_{1i} is the score improvement (a proxy for learning) of participant i, α_1 is the intercept, and β_1 is the coefficient measuring the effect of the instrument on the predicted value of the score improvement. IV_i is the instrument (mentor assignment). Finally, $\mathbf{X}_i$ is a vector of control variables for participants' demographic and business characteristics, and ε_{1i} is the residual of the first-stage model. In the second stage of the estimation, Y_i is a participant's business performance after graduating from the incubator. The variable α_2 is the intercept, β_2 is the effect of the predicted value of a participant's score improvement ($\hat{Z}_{1i}$) instrumented by mentors' ability, and $\mathbf{X}_i$ is the same vector of control variables as in the first-stage model. Finally, ε_{2i} is the residual of the second-stage model.

Three additional tests evaluated model specification: (1) a model under-identification test, (2) a model weak identification test, and (3) a model over-identification test.[6] First, the under-identification test evaluated whether the excluded instrument in the models (mentor ability) explained variation in the endogenous regressor (entrepreneur learning) (Baum et al. 2003, 2007, 2015). Under the null hypothesis that the model is under-identified, the matrix of reduced-form coefficients on the first-stage excluded instruments has rank K1-1, where K1 is the number of endogenous regressors. Under the null hypothesis, the test statistic has a chi-squared distribution with one degree of freedom for one endogenous regressor and one instrument. A rejection of the null hypothesis indicates that the matrix is full-column rank—i.e., the equation correctly identifies the model. Second, a weak-identification test evaluated whether the equation weakly identified the model—i.e., whether the instrument explained only a small part of the variance in the endogenous regressor. Weak identification can inflate the second-stage coefficients and overestimate the effects of the endogenous regressor (Stock et al. 2002, Stock and Yogo 2005). Stock and Yogo (2005) provide a set of critical values against which to test the Wald F-statistic and evaluate weakly identified models. For the specified models, this critical value is 5.53 for 25% maximal IV size. Test statistics above this threshold mean that the test rejects the null hypothesis of weak model identification. Third, the Sargan–Hansen test for model over-identification evaluated whether the model was over-identified (Hansen 1982, Sargan 1988). The alternative hypothesis is that the model is just-identified (i.e., that there are as many instruments as endogenous regressors), in which case, the test statistic is zero.

Measures

The models used several measures of participants' learning and business performance to evaluate the relationship between mentoring and performance improvements.

Pre-entry Knowledge. First, each participant's baseline exam performance (on a scale of 0–100) measured their baseline knowledge coming into the incubator. This score measured participants' understanding of basic business operations and management concepts, such as bookkeeping, operations, strategic planning, and sales and marketing—this score proxies for a participant's human capital, based on prior education and work experience.

Entrepreneurial Learning. Further, each participant's final exam score (on a scale of 0–100) measured their knowledge of the same material after completing the 24-week incubation program. This measure captured participants' *learning* by differencing their final scores from their baseline scores (*Score Improvement = Final Score – Baseline Score*) and taking the natural log of the result to adjust for skew.

Mentors' Ability. This study relied on prior studies that have used student exam score improvements as indicators of school and teacher effectiveness (Hoxby 2000, 2004). In keeping with this approach, this study operationalized mentors' ability as the lagged average score improvement of participants paired with each mentor in prior cohorts. Thus, mentors' ability measured mentors' demonstrated track records from work with participants from past cohorts.

Business Performance. Several variables measured business performance: monthly *business profits* (in Rand, logged), *sales revenue* (in Rand, logged), and *operating costs* (in Rand, logged). These metrics were collected over 12 consecutive months after participants graduated from the incubator.

Control Variables. Controls included participants' motivation to learn as the percent of in-class training sessions they attended during their time in the incubator. They also included participants' demographic characteristics, such as their *age* in years at the time of entering the incubator, their *gender* (male or female), their *nationality* (foreign-born versus native), and their program *dropout* status (whether they stopped participating in the program before graduating).

Finally, the models included several controls for peer effects within each cohort. The first was the *peer effect on learning*, the average score improvement of a participant's peers within the same cohort on a scale of 0%–100%, log-adjusted for skew. The second was the *peer effect on revenue*, measured as the average revenue of peers in the same cohort (in Rand, logged). The third was the *peer effect on profits*, measured as the average profitability of peers within the same cohort (in Rand, logged).

Study 2: Results and Discussion

Descriptive Statistics

Participants' average exam scores at baseline (a proxy for their human capital) was 6.64 points (out of 100 points), with a standard deviation of 4.31 points. By contrast, their final scores averaged 43.92 points (again, out of a maximum of 100 points), with a standard deviation of 11.65 points. The average score improvement over baseline was 37.278 points, with a standard deviation of about 10.86 points. The percent of in-class training sessions attended during the incubation program (a proxy for motivation) was 19.86, with a standard deviation of about 29. The average age of participants upon entry in the incubator was 33.51 years, with a standard deviation of 8.53 years. About 41% of these entrepreneurs were female and about 5.6% were foreign-born. Most participants completed the program, with only about 0.08% of all participants dropping out without graduating. The average profits of incubated businesses 12 months after graduating from the incubator were about 3,436 Rand per month (about \$232), with a standard deviation of 8,046 Rand (about \$544). The average revenue was about 7,202 Rand per month (about \$487), with a standard deviation of 16,518 Rand (about \$1,117). The average operating costs were about 3,766 Rand per month (about \$255), with a standard deviation of 10,179 Rand (about \$688). Approximately 92.52% of participants self-identified as black, 4.67% as colored, and the remainder as "other," including Indian and Asian.

Hypothesis Testing

Table 2 reports the results from models testing Hypothesis 2a and Hypothesis 2b. The results show that mentors' ability affected the magnitude of participants' learning during incubation. Further, learning predicted changes in participants' business performance after incubation. Model (5) shows that each percent increase in a participant's score improvement corresponded to a 3.250% ($t = 3.43$, $p < 0.001$) increase in monthly revenue. Model (6) shows that participants' score improvements increased by roughly 1.149% ($t = 11.80$, $p < 0.001$) for each percent increase in their mentors' ability. That is, participants paired at random with high-ability mentors learned more, as evidenced by their score improvements. Post-estimation tests of Model (5) rejected the null hypothesis that the model was under-identified (Kleibergen–Paap rk LM statistic = 64.149, χ^2 p-value = 0.000). Post-estimation tests of this model also rejected the null hypothesis that the model was weakly identified (Cragg–Donald Wald F statistic = 141.167). The R^2 was 0.73 (uncentered) and 0.42 (centered).

Model (7) further shows that each percent increase in a participant's score improvement during incubation predicted 3.519% ($t = 3.50$, $p < 0.001$) higher monthly profits after incubation. Model (8) also shows that, at the first stage of the estimation, each percent increase in mentors' ability corresponded to 1.108% larger score improvements over the 24-week incubation period ($t = 10.68$, $p < 0.001$). Post-estimation tests for Model (7) rejected the null hypothesis that the model was under-identified (Kleibergen–Paap rk LM statistic = 59.467, χ^2 p-value = 0.000). Post-estimation tests also rejected the null hypothesis that the model was weakly identified (Cragg–Donald Wald F statistic = 114.738). The R^2 was 0.68 (uncentered) and 0.36 (centered). The Sargan–Hansen J-statistics for models (5) and (7) were both zero, meaning that both models were exactly identified.

Table 3 reports the interaction effects between mentors' ability and participants' pre-entry knowledge and experience, testing Hypothesis 3. The models also include a set of interactions between mentors' ability and entrepreneurs' demographic characteristics, including gender and ethnicity. These models control for participants' nationality, program dropout status (attrition), individual motivation, and peer effects on learning (average score improvements for other participants in the same cohort). The baseline categories for these models are black, male, South African–born participants. As this table shows, the benefits of being paired with high ability mentors varied with participants' demographic characteristics. The main effects of model (9), for example, confirm the results from the primary analyses that participants paired with more capable mentors scored higher on their exit exams ($b = 45.67$, $p < 0.001$, $t = 10.89$), as did participants with higher human capital ($b = 6.262$, $p < 0.001$, $t = 6.39$), and greater motivation to learn ($b = 0.0464$, $p < 0.01$, $t = 2.77$).

Moderators

The interaction effects between mentors' ability and the moderators showed that the benefits of being

Table 2. 2SLS IV Regressions: Effect of Mentor Ability on Participant Learning and Performance

	(5)	(6)	(7)	(8)
	Second-stage 2SLS IV	First-stage 2SLS IV	Second-stage 2SLS IV	First-stage 2SLS IV
	Performance: *Business revenue* (Log, Rand), 12 months after incubation	Learning: *Score improvement* (Log, 0%–100%)	Performance: *Business profit* (Log, Rand), 12 months after incubation	Learning: *Score improvement* (Log, 0%–100%)
Hypothesis 2b: Learning: *Score improvement from baseline* (Log, 0%–100%)	3.250*** (3.43)		3.519*** (3.50)	
Hypothesis 2a: Mentor ability: *Lagged average score improvement of prior participants paired with the mentor* (Log)		1.149*** (11.80)		1.108*** (10.68)
Motivation: *Percent sessions attended* (0%–100%)	0.0451*** (4.15)	0.00274*** (4.06)	0.0366** (3.15)	0.00311*** (4.40)
Peer effects on learning: *Average score improvement in cohort* (Log, 0%–100%)	–0.0177 (–0.01)	–0.304 (–1.30)	–1.441 (–0.49)	–0.371 (–1.45)
Peer effects on revenue: *Average revenue in cohort after incubation* (Log, Rand)	0.208 (0.59)	0.00141 (0.05)	0.184 (0.50)	–0.00962 (–0.31)
Peer effects on profits: *Average profits in cohort after incubation* (Log, Rand)	–0.315 (–0.78)	0.00940 (0.29)	–0.00568 (–0.01)	0.0197 (0.56)
Intercept	–9.456 (–0.80)	1.117 (1.30)	–8.920 (–0.75)	1.584 (1.71)
Under-identification test (Kleibergen–Paap rk LM statistic)[a]	64.149		59.467	
$\chi^2(1)$ *P*-value	0.0000		0.0000	
Weak identification test (Cragg–Donald Wald F statistic)[b]	141.167		114.738	
Sargan–Hansen J statistic (over-identification test of all instruments)	0.000 (exactly identified)		0.000 (exactly identified)	
R^2 (uncentered)	0.73		0.68	
R^2 (centered)	0.42		0.36	
N	284	284	284	284

Notes. *t* statistics in parentheses. Baseline categories: black, male, South African–born entrepreneurs. All models include controls for participants' age, gender, nationality, ethnicity, baseline exam score (human capital), program dropout status (attrition), the quarter reported for performance data (seasonality), and operating costs (a proxy for firm size). Log denotes the natural logarithm.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$ (two-tailed tests).

[a]H0: Matrix of reduced form coefficients has rank = K1-1 (under-identified).

[b]H0: The equation is weakly identified.

paired with high-ability mentors decreased with participants' pre-entry knowledge (baseline exam score) and experience (age at the time of participating). Model (9) shows that the benefits of being paired with high-ability mentors were lower for participants with higher baseline scores coming into the incubator ($b = –1.474$, $p < 0.001$, $t = –5.48$). Further, as model (10) shows, the benefits of being paired with high-ability mentors were more significant for minority participants ($b = 53.98$, $p < 0.01$, $t = 3.07$), who had lower baseline exam scores coming into the incubator ($b = –198.6$, $p < 0.01$, $t = –3.10$). Additionally, as the results of model (11) show, the benefits of being paired with high-ability mentors were lower for older participants who had more prior work experience ($b = –0.425$, $p < 0.01$, $t = –2.90$), whose baseline scores were higher than for younger participants ($b = 1.532$, $p < 0.01$, $t = 2.92$). Finally, as the results of model (12) show, the benefits of being paired with high-ability mentors were lower for female than male participants ($b = –18.83$, $p < 0.001$, $t = –4.12$), because women had higher baseline exam scores coming into the incubator ($b = 68.95$, $p < 0.01$, $t = 4.18$). These results suggest that women entrepreneurs in this incubator were, on average, more knowledgeable about startup management than their male counterparts. These results could be attributable to stronger selection pressures affecting women entrepreneurs, which could have increased the quality of female applicants and participants in the incubator. Overall, models (9)–(12) explain between 47% and 50% of the total variance in outcomes across all participants in the incubator.

Table 3. Moderators of the Benefits of Mentoring

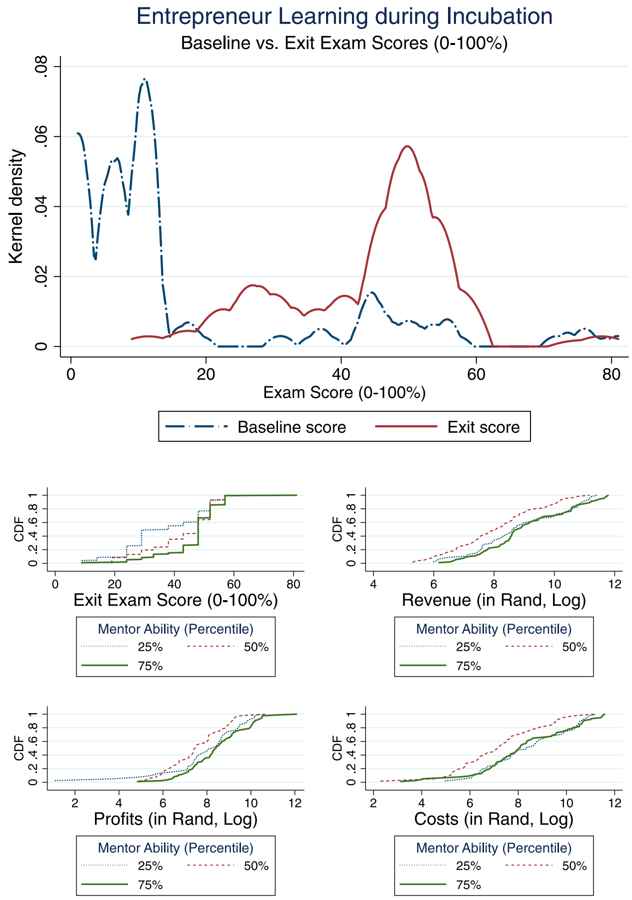
	(9)	(10)	(11)	(12)
	Moderator: *Pre-entry knowledge*	Moderator: *Ethnicity*	Moderator: *Age*	Moderator: *Gender*
	Exit exam score (0%–100%)	*Exit exam score* (0%–100%)	*Exit exam score* (0%–100%)	*Exit exam score* (0%–100%)
Mentor ability: *Lagged average score improvement of prior participants paired with the mentor* (Log)	45.67*** (10.89)	25.15*** (12.33)	46.42*** (6.18)	40.97*** (9.55)
Pre-entry knowledge: *Participant's baseline score* (0%–100%)	6.262*** (6.39)	0.894*** (8.21)	0.894*** (8.17)	0.944*** (8.75)
Hypothesis 3: *Mentor ability × Pre-entry knowledge*	−1.474*** (−5.48)			
Ethnicity: *Coloured*	−2.420 (−1.39)	−198.6** (−3.10)	−2.447 (−1.36)	−2.467 (−1.45)
Mentor ability × Coloured		53.98** (3.07)		
Entrepreneur age	−0.0161 (−0.29)		1.532** (2.92)	
Mentor ability × Age			−0.425** (−2.90)	
Gender: *Female*	1.265 (1.25)	1.464 (1.50)	0.912 (0.88)	68.95*** (4.18)
Mentor ability × Female				−18.83*** (−4.12)
Nationality: *Foreign-born*	0.543 (0.25)	2.012 (0.89)	1.346 (0.59)	0.984 (0.44)
Status: *Program dropout (attrition)*	18.18** (2.86)	15.89* (2.44)	15.27* (2.34)	17.21** (2.67)
Motivation: *Percent sessions attended* (0%–100%)	0.0464** (2.77)	0.0492** (2.86)	0.0510** (2.96)	0.0509** (2.99)
Peer effects on learning: *Average score improvement in the cohort* (Log, 0%–100%)	6.129 (1.05)	7.942 (1.33)	7.816 (1.30)	6.868 (1.16)
Intercept	−149.6*** (−6.84)	−82.40*** (−4.10)	−158.5*** (−5.29)	−135.8*** (−6.12)
Adjusted R^2	0.50	0.48	0.47	0.49
N	284	284	284	284

Notes. t statistics in parentheses. Log denotes the natural logarithm.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$ (two-tailed tests).

Figure 3 plots the effects of mentors' ability on entrepreneur learning and post-incubation business performance. As the kernel density plot shows, there was a shift in the distribution of exam scores for participants in the incubator between their baseline exam performance (dashed line) and their exit exam performance (solid line). The exit scores were higher on average. This shift suggests that participants improved their comprehension of core knowledge and skills tested on these exams, including how to scale operations and grow revenue, during their time in the incubator.

Further, as the cumulative distribution function (CDF) plots show, mentors' ability explained the variance in exit exam scores and subsequent business performance. The CDF of exit exam scores for participants assigned to mentors in the 75th percentile of ability stochastically dominated the CDF of exit exam scores for participants assigned to mentors in the 25th percentile of ability. Further, the CDFs of subsequent business performance (revenue and profits) for participants assigned to mentors in the 75th percentile of ability also stochastically dominated the CDF of business performance for participants assigned to mentors in the 25th percentile of ability. These results suggest that participants' final exam scores and business performance after incubation increased with their mentors' expertise.

Figure 3. (Color online) Effects of Mentoring on Entrepreneur Learning and Performance



CDF - cumulative distribution functions (empirical). Log denotes the natural log.

Discussion

Entrepreneurs from disadvantaged backgrounds often experience lower growth and profitability for their businesses (Fairlie and Robb 2009, Field et al. 2010, McKenzie and Woodruff 2016). Recent studies have sought to identify interventions that can bridge these gaps by providing support for entrepreneurs from disadvantaged backgrounds, including in-class training, cash grants, and free management consulting (Fiala 2013, Dyer et al. 2016, Anderson et al. 2018). The premise has been that targeted interventions fill gaps in human capital and enable entrepreneurs from disadvantaged backgrounds to realize higher growth and profitability for their businesses.

This study has sought to contribute to this line of research by examining interventions that promote learning, scaling and profitability among socially and educationally disadvantaged entrepreneurs. Specifically, the focus was to evaluate the benefits of incubation and personalized mentoring for helping disadvantaged entrepreneurs supplement gaps in their pre-entry knowledge and experience that can arise from limited educational and employment opportunities (Dencker et al. 2009, Unger et al. 2011, McKenzie and Woodruff 2014).

The findings showed that both incubation and mentoring were beneficial for improving the performance of businesses founded by disadvantaged entrepreneurs. Further, the benefits of being mentored depends on entrepreneurs' prior knowledge and experience. Mentoring was more useful for increasing learning among entrepreneurs who had less prior knowledge and experience, and translated into higher performance improvements for their businesses. The findings also showed that incubation was beneficial for supporting revenue and employment growth, often associated with greater societal and economic value creation from entrepreneurship (Robinson 2010, Akçomak 2011, Dutt et al. 2016).

Theoretical Contributions

The findings contribute to several areas of research. First, they contribute to research on the benefits of venture incubators and accelerators for entrepreneurial learning and early-stage startup development (Yu 2015, Lasrado et al. 2016, Cohen et al. 2019a). The existing literature has called for examining how selection into incubators affects startup outcomes and what role these organizations play in supporting founders and their startups (Hackett and Dilts 2004, Phan et al. 2005). This study contributes to this literature by showing that being incubated was associated with higher sales and employment growth over time for businesses founded by disadvantaged entrepreneurs with limited pre-entry knowledge and experience. This study, therefore, finds support for the benefits of venture incubation and mentoring for entrepreneurs beyond the contexts examined in prior studies that focus on high-human-capital individuals (Hallen et al. 2014, Lasrado et al. 2016).

Second, this study contributes to the literature on human capital and entrepreneurial success (van der Sluis and van Praag 2007, Fairlie and Robb 2009, Unger et al. 2011). Existing studies of human capital in entrepreneurship have focused on path-dependent labor market processes and educational backgrounds (Shane and Stuart 2002, Beckman and Burton 2008, Baptista et al. 2014). The managerial capital literature, however, has shown that skills and knowledge can be developed through in-class training or imported through outside consulting to improve business performance (Bloom et al. 2013a, 2013b; Anderson et al. 2018). This study contributes to this literature by evaluating the benefits of entrepreneurs' learning during incubation on subsequent business performance. The findings showed that venture incubation and mentoring were associated with business development among disadvantaged entrepreneurs and contributed to increases in business revenue and profits.

Third, this study adds to the literature examining interventions to help improve the business growth and performance of disadvantaged entrepreneurs (McKenzie and Woodruff 2016, Anderson et al. 2018, Bruhn et al. 2018). The findings showed that mentoring was beneficial for bridging gaps in knowledge and experience for entrepreneurs facing social and economic inequities. Further, mentoring was more beneficial for entrepreneurs with less prior knowledge and experience. These findings suggest that mentoring is useful because it supplements gaps in entrepreneurs' prior knowledge and experience, particularly for underrepresented minorities that have a harder time obtaining the resources they need to launch and scale their businesses (Younkin and Kuppuswamy 2018, 2019).

Limitations and Future Directions

This study has several limitations. First, the generalizability of these findings is limited because both studies focused on a single incubator in South Africa. More evidence is needed before we can comfortably conclude that incubation is beneficial for different types of entrepreneurs and various types of businesses. Second, although the evidence suggests that mentoring was especially helpful for entrepreneurs with less pre-entry knowledge and experience coming into the incubator, more evidence is needed to understand why mentoring was less beneficial for female entrepreneurs in this incubator than for male entrepreneurs.

The observed differences in the benefits of mentoring for entrepreneurs from different demographic groups could be attributable to stronger selection pressures for ethnic minority and female entrepreneurs that apply to venture accelerators. For example, stronger selection pressures for women entrepreneurs could have resulted in female participants having more pre-entry knowledge about startup management coming into the incubator than their male counterparts. More studies are needed to assess the mechanisms producing these differences in pre-entry knowledge and the benefits of mentoring for entrepreneurial learning. Thus, readers should interpret the findings in light of these limitations as offering preliminary evidence that mentoring is associated with increases in entrepreneurial learning and with revenue and profit growth for entrepreneurs with limited formal education and prior work experience.

Policy Implications

This research provides several policy implications for entrepreneurs, incubators, and governments. First, it suggests that entrepreneurs should be aware of how their pre-entry knowledge and experience affect their business performance. This awareness can limit the misattribution of poor performance to other factors, such as innate ability. Further, understanding incubators' role in supporting entrepreneurial learning through mentoring could encourage more disadvantaged entrepreneurs to apply for these resources. The evidence suggests that these learning support resources are immensely valuable for supplementing entrepreneurs' gaps in pre-entry knowledge and experience.

Second, this research indicates that incubators should focus on investing resources in recruiting, hiring, and developing talented mentors to offer feedback to entrepreneurs. Mentors are vital to the value that incubators and accelerators provide as centers of entrepreneurial learning. Lastly, for governments, this research suggests that funding organizational sponsors of early-stage ventures, such as incubators, and supporting mentoring programs within these organizations might be worthwhile activities to equalize the playing field for disadvantaged entrepreneurs. These resources can help entrepreneurs from socially and educationally disadvantaged backgrounds obtain valuable advice, knowledge, and insight from qualified mentors. Thereby, incubators could help disadvantaged entrepreneurs overcome significant impediments to entrepreneurial learning and successful entrepreneurship, such as gaps in pre-entry knowledge and experience. By investing resources to support these entrepreneurs and their businesses, governments can expand their capacity to create jobs and catalyze economic growth through entrepreneurship.

Conclusion

Early-stage venture incubators provide powerful tools that can help socially and educationally disadvantaged entrepreneurs develop their businesses. Disadvantaged entrepreneurs often face multiple impediments to growing and scaling their businesses, beyond the usual challenges of being under-funded, which can limit their ability to be successful. These impediments include bounded rationality, limited resources to experiment, and limited pre-entry knowledge and experience, all of which can arise from structural inequality, poverty, and social discrimination. The combination of these factors can result in low growth and business performance, despite entrepreneurs' desire to grow their businesses. The findings from this research suggest that incubators can help disadvantaged entrepreneurs achieve profitability and scale for their businesses, through a combination of incubation and supervised learning support, such as personalized mentoring. When provided alongside other resources, personalized mentoring can develop entrepreneurs' knowledge and capacity to manage and grow their operations, increasing both scale and profitability. Incubators can impart potentially long-lasting benefits to disadvantaged entrepreneurs that enable them to overcome impediments to learning and develop successful ventures. The insights from this study, therefore, support the adage that teaching people new knowledge and skills can sometimes be far more effective at helping them succeed than giving them only tangible resources that have limited power to transform their lives.

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Endnotes
[1] By comparison, the typical response rates for phone surveys conducted in the United States is around 9%, according to the Pew Institute.

[2] The geodesic distance on an ellipsoid between an applicant's home address and the latitude and longitude coordinates of the incubator was estimated in Stata 15 SE using the **geodist** function. This function uses the Vincenty (1975) equations when computing distances on a reference ellipsoid, the WGS 1984 datum that GPS devices and Google Earth/Map currently use.

[3] The residuals are the difference between the actual distance from an applicant's home address to the incubator's address and the distance predicted from applicants' age, ethnicity, gender, and business performance (sales revenue, operating costs, profits) at the time of applying.

[4] This formula is mathematically equivalent to the difference in the log-adjusted performance at T1 relative to T0, which is $log(x_{t1}) - log(x_{t0})$, where log denotes the natural logarithm.

[5] Individuals who self-identified as black are a majority group in South Africa, representing 80.2% of the total population. The other categories are Other/Unspecified (0.5% of the total population) and Indian/Asian (2.5% of the total population).

[6] The models do not report the Wu–Hausman test (also known as the Durbin–Wu–Hausman test) because this test is not valid for robust covariance estimators as the one used in the 2SLS IV models (Baum et al. 2003, 2007, 2015). The Wu–Hausman compares the IV and OLS estimates under the assumption of conditional homoskedasticity for the same models to determine whether the estimates are similar. If they are, then there is insufficient evidence to reject the null hypothesis that the endogenous variable (i.e., entrepreneur learning) could be treated as exogenous to derive consistent estimates. Conditional homoskedasticity means that the second moment of the error terms $E(\varepsilon_i^2)$ is constant across the observations (i.e., entrepreneurs), an assumption that does not hold in the sample.

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