Are the United Nations Sustainable Development Goals a comprehensive guideline to conceptualise a Wellbeing Economy?

A Case Study of the Dutch Good Growth Fund's Impact on Local Employment Objectives

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Student Name: Rutger de Roo van Alderwerelt
Student ID: 406414rr

Supervisors: Prof. Dr. (Mary) Pieterse-Bloem (ESE)
Andres van der Linden (Triple Jump)
Second Assessor: Prof. Dr. (Onno) Steenbeek (ESE)

Institution: Erasmus University Rotterdam
Faculty: Erasmus School of Economics

ABSTRACT

In 2017, the Wellbeing Economy Alliance launched a movement that aims to transform the current economic system into a system that is centred around human and ecological wellbeing, defined as a *Wellbeing Economy*. In this research, I explore whether the *United Nations Sustainable Development Goals* provide a unified guideline to conceptualise economic wellbeing. *Foreign Direct Investments* are believed to play a key role in the achievement of the *United Nations Sustainable Development Goals*, and, therefore, offer a prominent perspective on the research question. I perform a thorough qualitative and quantitative analysis of the integration of these goals in the recently developed *Social Impact Investment* market. In this market, *Sustainable Development Goal* 8 is found to be the most prominent target impact objective, as investors aim to contribute to local employment objectives and overall economic growth. More specifically, I conduct a case study of the *Dutch Good Growth Fund's* data for financing *Small to Medium Enterprises,* on three employment demographics, *Female- and Youth Employment (*ages *18 – 24* and *25 – 35).* I find evidence that *Female Employment* is positively and significantly affected by the investment, but I cannot conclude that this is true for both *Youth Employment* age groups. Diving more into the dataset finds significant differences between countries, regions and sectors, in the change in these employment demographics. These findings are illustrative of the positive impact the *Dutch Good Growth Fund* can achieve through financing *Small to Medium Enterprises* and thereby contributing to the achievement of the *United Nations Sustainable Development Goals.* This leads to the discussion of this research that, in this market, these goals offer a comprehensive guideline to investors to target impact objectives. As a result, this leads to the conclusion that this can contribute to further conceptualise and develop a human and ecological wellbeing-centred economic system.

Key Words: Wellbeing Economy, United Nations, Sustainable Development Goals, Foreign Direct Investments, Social Impact Investment, Dutch Good Growth Fund, Small to Medium Enterprises, Female- and Youth Employment

FOREWORD

Last year, I decided to postpone my MSc thesis for a year, to carefully explore socially relevant research topics that would contribute to modern economic thinking. My first concrete steps were taken in December 2019, when I approached the Wellbeing Economy Alliance to learn about the knowledge gaps that exist in conceptualising a *Wellbeing Economy*. I received a positive response with many topics that I further explored but found it hard to find sufficient data. Due to my experience, working for the Dutch development bank, and previously writing my BSc thesis about the effects of foreign direct investments, I ended up contacting multiple professionals in the field of development finance and impact investing. The United Nations Sustainable Development Goals and their relevance towards conceptualising a wellbeing economy quickly came on to my radar. The research question that followed can be explored in many ways and I strongly recognize this will be a large opportunity in future academic research, especially, for young academics. I hope this research will enthuse more economics students and young academics to research topics beyond traditional economic thinking and challenge themselves in topics that are topical and more relevant to today's society. It is not an easy road, and data may be challenging to find. However, as the social impact investment market matures and more unified methodologies for impact measurement and analysis are devised, more and better data will become available.

I would not have been able to develop my thesis without the continued support of a large number of people. Most importantly, the insights I received from multiple professionals at Triple Jump, Oikocredit and FMO were invaluable to my thesis. Andres, Mitzi and Corianne, without the insights you provided from your roles in your respective companies, I would not have known what scope I should have taken to further develop my research. You guided me through relevant existing literature that you use in your profession that otherwise would maybe not have reached my radar. Andres, thank you for providing me with the data from the *DGGF*, and your guidance through it. Without it, this thesis would not have existed.

A special thanks to Charles Hermans, my old colleague at ESE and friend, for putting me into contact with Andres at Triple Jump.

I am also very grateful for the continued enthusiasm and support of my supervisor, Mary (Prof. Pieterse-Bloem), especially when I first approached you with my optimistic ideas in February 2020.

Finally, I want to thank my family for both mental support and the discussions throughout the past few months, but also my entire life. I would never be where I am today without you.

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Abbreviations (In order of appearance)

UN – United Nations
SDGs – Sustainable Development Goals
FDI – Foreign Direct Investment
OECD – Organisation for Economic Co-operation and Development
UNCTAD – United Nations Conference on Trade and Development
SII – Social Impact Investment
WEAll – Wellbeing Economy Alliance
GDP – Gross Domestic Product
USA – United States of America
FMO – Financierings-Maatschappij voor Ontwikkelingslanden
TJ – Triple Jump
Oiko – Oikocredit
DGGF – Dutch Good Growth Fund
SMEs – Small to Medium Enterprises
GIIN – Global Impact Investment Network
DFIs – Development Finance Institutions
NGOs – Non-Governmental Organisations
ESG – Environmental, Social and Governance
RI – Responsible Investment
GPI - Genuine Progress Indicator
HDI - Human Development Index
MNCs – Multinational Corporations
MFIs – Microfinance Institutions
MDGs – Millennium Development Goals
SDGI – Sustainable Development Goals Initiative
DNB – De Nederlandsche Bank
APG – Algemene Pensioen Groep N.V.
PGGM – Pensioenfonds voor de Gezondheid, Geestelijke en Maatschappelijke belangen
SDI – Sustainable Development Investments
ATL – Acknowledged Transformational Leader
EDFI – European Development Finance Institutions
IFC – International Finance Corporation
AUM – Assets Under Management
ILO – International Labour Organisation
IRR – Internal Rate of Return
WBD – World Bank Database

1. Introduction

1.1. United Nations Sustainable Development Goals

In 2015, member states of the United Nations (UN) established the Sustainable Development Goals (SDGs) to achieve 17 ambitious objectives by 2030 that would tackle the global issues of this time. Inequalities, climate change, fossil fuels, education levels, world hunger among others are all widely discussed topics everywhere, in politics, academics, and on social media. If, or I should better say when, these goals are achieved, the world will have a more sustainable system in place that allows human and ecological wellbeing to be at the centre of our socio-economic activities. All goals have their own focus area, where each is explored in more detail through specific SDG targets (United Nations, 2015). Simply by observing all SDGs, one can recognize certain degrees of commonality between them, meaning that the solutions to one goal may go hand-in-hand with those of another. In **Table 1**, all 17 goals are presented.

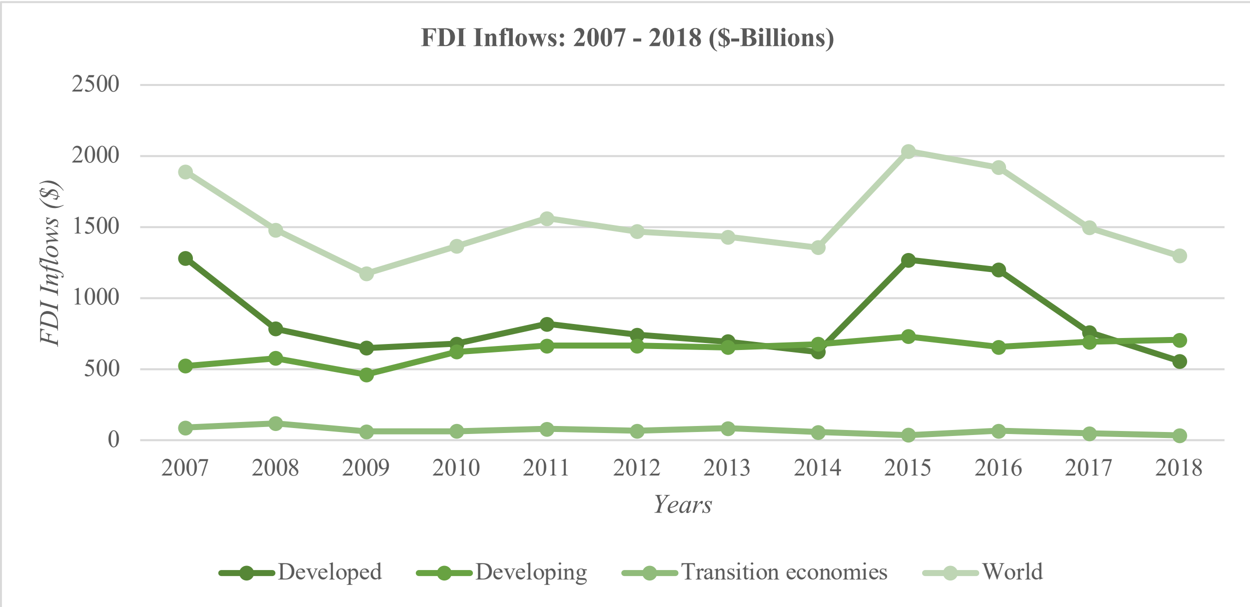
The 17 UN Sustainable Development Goals	
1 – No Poverty	10 – Reduced Inequalities
2 – Zero Hunger	11 –Sustainable Cities and Communities
3 – Good Health and Wellbeing	12 – Responsible Consumption and Production
4 – Quality Education	13 – Climate Action
5 – Gender Equality	14 – Life Below Water
6 – Clean Water and Sanitation	15 – Life on Land
7 – Affordable and Clean Energy	16 – Peace, Justice and Strong Institutions
8 – Decent Work and Economic Growth	17 – Partnerships for the Goals
9 – Industry, Innovation, and Infrastructure	

Table 1: Overview of UN SDGs (For a more detailed description, see Appendix A, Table A1, P.68

To evaluate progress on each goal, the UN tracks 232 unique indicators and, if data is available, their results are published via an SDG-tracker (Roser, Ortiz-Ospina, & Ritchie, 2018). It is crucial to regularly evaluate the achievability of the SDGs, however, there is an ongoing discussion on how this should be done. Even though the UN presents multiple indicators per goal, they are usually only output measures. It is important to investigate more closely what the outcomes are of these different output measures to determine their contribution to the SDGs. The primary thought behind the UN SDG framework is to "*Leave No One Behind",* by focussing on developing countries and emerging markets, which are highly affected by current global issues. In other words, the UN supports the idea that countries should assist each other, both financially and non-financially, to realise the SDGs by 2030.

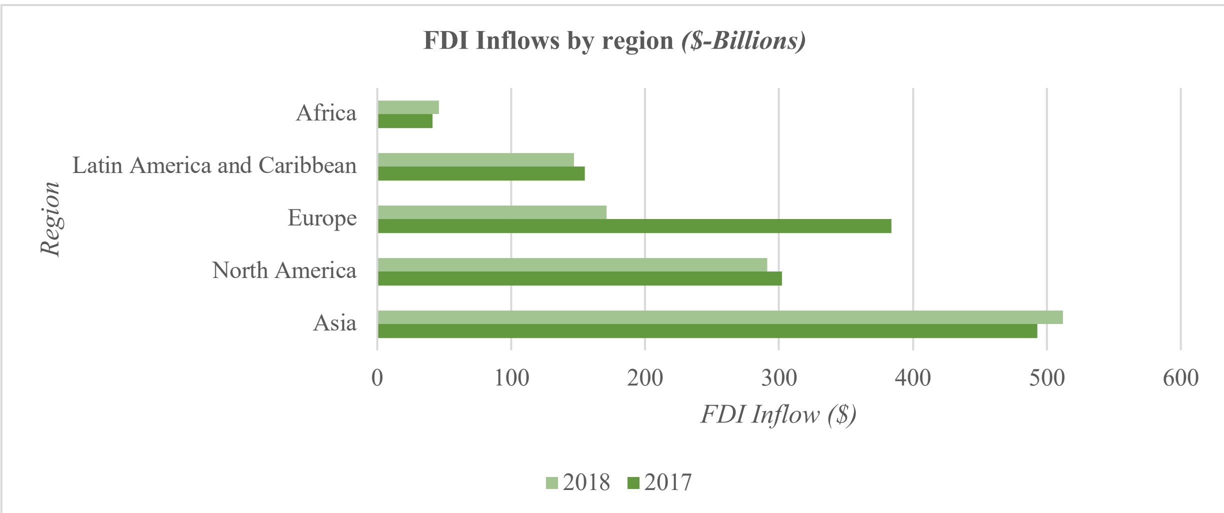
One channel through which countries can and have helped other countries is by Foreign Direct Investment (FDI). In fact, the Organisation for Economic Co-operation and Development (OECD) has identified FDI as one of the primary contributors to the achievement of SDGs in developing countries and emerging markets (Gestrin, 2016). Intuitively, one would expect that, since the establishment of the SDGs, FDI levels have increased. In 2015, global FDI flows were the highest ever recorded since the 2008 financial crisis, increasing by 38% relative to 2014 (UNCTAD, 2016). However, in the years after, global FDI flows have slipped annually as can be seen in **Graph 1**. A 13% decrease in 2016, followed by 16% in 2017, 20% in 2018, but only 1% in 2019 (UNCTAD,

2017; UNCTAD, 2018; UNCTAD, 2019; UNCTAD, 2020)[1]. This trend was mainly driven by decreases in FDI inflow in developed countries, while in developing countries it remained more stable.



Graph 1: Overview of FDI Inflows 2007 – 2018 (Source: (UNCTAD, 2019)**)**

As one can derive from **Graph 1,** developing countries have experienced a slight increase in 2017 and 2018, 5% and 2% respectively. In the category of developing countries, the UNCTAD distinguishes between developing countries in Africa, Asia and Latin America. According to the World Investment Report, published by the UNCTAD in 2019, Africa received the lowest amount of FDI in both 2017 and 2018, relative to the other developing regions, as can be seen in **Graph 2.**



Graph 2: Overview of FDI Inflows by region (Source: (UNCTAD, 2019)**)**

[1] UNCTAD = United Nations Conference on Trade and Development

There are many reasons that could clarify why Africa is less attractive for FDI than the other developing regions. FDI inflow is dependent on specific geographic, economic and political conditions, such as natural resources, human capital, liberalized markets and political stability (Borensztein, De Gregorio, & Lee, 1998). In light of the suggestion that FDI should be a main contributor to the achievement of SDGs, one could argue that only looking at the level of FDI is not sufficient. One cannot, simply, derive from levels of FDI flows, whether it contributes to a region's achievability of the SDGs. It could be more valuable to explore what impact FDI has, using socio-economic and environmental indicators as an output measure, on the achievability of the SDGs. Subsequently, I argue that this can be translated into an economic model that is based on human and ecological wellbeing. This could be evident due to the prominence of the SDGs in the development of the *Social Impact Investment (SII)* market. I will further elaborate on this market in Chapter 2. In the following Section I briefly introduce the concept of a Wellbeing Economy and its increasing global support.

1.2. A Wellbeing Economy System

In 2017, the Governments of Scotland, Costa Rica, New Zealand and Slovenia formed the *Wellbeing Economy Alliance (WEAll)* and introduced the concept of a *wellbeing economy. WEAll* advocates for an economic system that is measured by indicators that represent human and ecological wellbeing. Their aim is to reshape the economy so that *"humanity determines the economy and not let the economy determine humanity"* (Wellbeing Economy Alliance, 2020). In other words, if we would align our definition of overall economic prosperity more with factors that measure socio-economic and environmental impact, then we might be able to transform the current economic system into a *Wellbeing Economy* system.

Leaders of *WEAll* affiliated countries have expressed the need to move our focus away from gross domestic product (GDP), and start looking at social indicators that capture variables that shape modern societies (BBC, 2019). Joseph Stiglitz, a Nobel laureate in economics, has similarly argued that metrics such as GDP fail to capture variables, like climate change, inequality and social welfare. In addition, Angel Gurría, the secretary general of the OECD, wrote that "*It is only by having better metrics that truly reflect people's lives and aspirations that we will be able to design and implement better policies for better lives".* It is argued by Stiglitz (2019) that these traditional measures of economic performance lead to widespread political discontent. It has become apparent that, even when GDP is increasing, it does not mean the population's wellbeing is increasing. This is also true for other economic measures, such as the stock market and the unemployment rate.

United States (USA) President Donald J. Trump recently claimed that the current American economy is booming, which results in America and Americans doing great. The economic figures used to substantiate his claim are a record low unemployment rate and high stock market gains (World Economic Forum, 2020; Associated Press, 2020). Indeed, over the past 5 years the USA unemployment rate decreased from 5% to 3.5% (U.S. Bureau of Labor Statistics, 2020). In addition, in the year 2019, stock market gains, based on the delivery of the S&P 500, were larger than 28% (Lewis, 2019). These figures are undisputed facts. However, it is argued that these economic measures are not illustrative of a people's wellbeing (Yukelson, 2018). During a panel, *The Cost of Inequality,* at the World Economic Forum in 2019, Winnie Byanyima, Executive Director of Oxfam International, stated that only looking at the unemployment rate does not encompass the dignity and quality of those jobs. In addition, the stock market has been used, historically, as an important indicator for the state of an economy (Amadeo, 2019). However, the question that many ask is whether everyone benefits from a stock market increase, or if that is just limited to a certain group of a population. Edward Wolff (2017) found that about 85% of stocks owned by U.S. households are held by the wealthiest 10% Americans. In his own words "*For most Americans, a stock price increase is pretty immaterial to their wellbeing*".

In addition, a recent book, *Doughnut Economics: Seven ways to Think Like a 21st-Century Economist* by Kate Raworth, elaborates on a new perspective of economic thought by including socio-economic and environmental factors that supposedly meet the needs of the 21st century, such as *employment, education, health, and the climate.*[2] This theory will be further explored in Section 3.1. All of the above indicates that there is a profound global sentiment that aims to stimulate a new kind of economic thinking that captures the global issues of this time. The SDGs aim to tackle these issues and should develop sustainable solutions. Therefore, I present the following research question that this research will explore:

Are the United Nations Sustainable Development Goals a comprehensive guideline to conceptualise a Wellbeing Economy?

To answer this question, I approached *WEAll*, whom advised on the directions that need to be taken to help conceptualize a *wellbeing economy*. In addition, I contacted a number of Dutch impact investors, the *Dutch Development Bank (FMO[3]), Triple Jump (TJ*) and *Oikocredit (Oiko)*, whom have all given valuable insights into the integration of SDGs in their investment portfolios and made a number of suggestions for my research. Based on their advice, and investment data retrieved from the *Dutch Good Growth Fund (DGGF)*, obtained via *TJ,* this research will conduct a case study on the impact of financing SMEs on three employment objectives; female and youth employment (18 – 24 and 25 – 35).

This research is divided into multiple chapters with (sub)-Sections aimed at providing the reader with a comprehensive overview of the context in which this research is conducted. First, I define *SII*, introduce trends in the *SII* market and discuss its relatability with the SDGs in Chapter 2. This will start the development of the scope of this research, primarily focussing on employment objectives of impact investors in Small to Medium Enterprises (SMEs), which aligns with SDG 8 (*Decent Work & Economic Growth*). Chapter 3 presents a number of literatures relevant to the context in which I develop the hypotheses of this research. I start with a review of academic literature on the history of *welfare* and *economic growth,* followed by academic literature on FDI's relationship with *employment* and *economic growth.* Furthermore, I review the research landscape of the *SII* market, followed by a review of literature on SME finance. This further details the scope and introduces the hypotheses of this research. In Chapter 4, I describe the data of the *DGGF* that is used, and present the statistical methodology applied to test the hypotheses. Chapter 5 contains the presentation of the main results, their interpretations and implications. Chapter 6 discusses the main findings and limitations, and it concludes this research by proposing areas for future research.

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[2] For a diagram of a Doughnut Economy see Appendix A, Figure A1, P.68
[3] Financierings-Maatschappij voor Ontwikkelingslanden

2. Social Impact Investment

2.1. Defining Social Impact Investment

Daggers & Nicholls (2016) identify that, in *SII*, there is a distinction to be made between *social investment* and *impact investment*. They critique the fact that these two terms are commonly used interchangeably, even though they should be defined as two separate concepts. This, however, does not mean that we need to talk about a social investment market and impact investment market. The two terms co-exist within the same *SII* market. The definitions of the two terms, as clarified by Daggers & Nicholls (2016) are shown in **Table 2.** The main difference lies in the perspective through which the objectives are measured. In social investment, it is a prerequisite that the recipient has pre-existing social objectives. In impact investment the investor pursues social goals, primarily through their own pre-determined social objectives, regardless of whether the recipient has such objectives.

Impact Investment vs. Social Investment	
Impact Investment	Investor behaviour and motivation approach: Investment activity that aims to create social and/or environmental impact either through direct allocation of capital or though intermediary financiers.
Social Investment	Investee behaviour approach: Investment activity that aims to create social and/or environmental impact through providing access to repayable capital to existing social sector organisations.

Table 2: Definitions of Social Impact Investment (Source: Daggers & Nicholls (2016))

It would be unwise to focus only on social investment for this paper, as it may be difficult to find sufficient data in developing countries. This is mainly true because, in developing countries, the social sector is often not sufficiently established. For the purpose of this research, I will use the term *impact investment* to refer to investment activity in the *SII* market. Based on the investment activity illustrated by the data from the *DGGF*, this research will focus on *impact investment.* In Chapter 4, I further elaborate on the investment data. Furthermore, *impact investment* is the primary terminology used by the Global Impact Investing Network (GIIN) in their reports about the *SII* market.

2.2. The Social Impact Investment Market

In 2007, the term *impact investing* first appeared and made its trademark in the development of the *SII* market. Key players in this market are *development finance institutions (DFIs), fund managers, individual investors, Non-Governmental Organisations (NGOs), diversified investment banks, foundations, etc.,* and they mostly invest in developing countries or emerging markets (GIIN, 2020). Impact investors mean to combine measurable social benefits with financial return (OECD, 2015). Primarily, *impact investors* are based in developed markets, such as Northern America and Europe (excl. Eastern Europe) and operate in developing regions, such as Africa, Asia and Latin America (GIIN, 2019). They are committed to generating social and environmental impact, through implementing environmental, social and governance (ESGs) factors in their investment decisions (Triple Jump, 2020). This, in turn, is defined as a responsible investment (RI) strategy.

At the end of 2018, the global *SII* market value was $502 billion, owned by an estimated 1.340 organisations. To put that in perspective, the OECD highlighted that, to achieve the SDGs, the *SII* market value should increase 10x its current market value to approximately $ 4-$5 trillion. One should not derive from this that with the current market value there is no significant impact measurable. In the contrary, GIIN (2019) indicates that there is a significant amount of capital in the *SII* market that addresses global socio-economic and environmental issues. Based on a survey among impact investors (n=278), GIIN (2020) identifies 16 unique impact target categories and bundles the remainder in *others*. **Table 3** presents the top 8 impact categories that more than 50% of respondents reported as an investment target[4]. It should be noted that it was possible for respondents to choose multiple impact categories. For example, they found that more than 70% of investors that target the agriculture category, also target employment (79%), energy (74%) and financial services (72%). Furthermore, they provided evidence that *impact investors* significantly combine categories such as health, education, and housing.

Target Impact Categories

Impact Category	*Percentage Targeted*
Employment	71%
Agriculture	63%
Financial Services	62%
Diversity and Inclusion, including gender and racial equity	60%
Health	60%
Education	56%
Energy	56%
Climate	54%

Table 3: Target Impact Categories with >50% respondents

Modified from Figure 11: Target Impact Categories in The State of Impact Measurement and Management Practice, GIIN (2020.

It can also be observed from **Table 3** that the impact categories align with a number of SDGs. In addition, one could argue that these categories also align with the basic concepts of a *doughnut economy* and could help conceptualise a *wellbeing economy. Employment* is the most targeted impact category among impact investors. It is for that reason that I wanted to find impact investment data on employment indicators. Impact investors, such as *FMO, TJ* and *Oiko*, prominently use SDGs as a reference to determine their investment objectives and impact measurements (OECD, 2015; IFC, 2018; Triple Jump, 2018; Oikocredit, 2019; FMO, 2020). This research aims to evaluate the impact of the capital invested by the *DGGF,* and its financial intermediaries, in SMEs and the resulting contribution to achieving SDGs. The evaluation will primarily be around SDG 8, as it directly relates to employment and simultaneously, economic growth[5]. Additionally, I will attempt to relate *DGGF's* contribution to other SDGs in Chapter 6.

[4] For the full table, published by GIIN (2020), see Appendix A, Table A2, P. 69

[5] In a more recently published impact investor survey for 2020, by GIIN (2020), SDGs are even used as a reference, instead of the impact categories referred to in **Table 3.** In that survey, SDG 8 was found to be the most prominent SDG that impact investors aim to contribute to. Another fact that substantiates my decision to focus on SDG 8.

2.3. SDG 8: Economic Growth and Decent Work

Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.

It can be derived from SDG 8 that there is a common consensus about a close relationship between *employment* and *economic growth*. The UN identified 12 individual targets that should help achieve this goal[6]. From these targets, it can be observed that there are many ways in which SDG 8 can be achieved. Too many to discuss all in this research. Evidently, the question arises, which one is most interesting. The truth is, all of them are incredibly relevant and interesting to investigate. Impact reports, conducted by *TJ* and *Oiko,* indicate that in contributing to SDG 8, most of their capital invested is allocated to SMEs, either directly or through financial intermediaries (Triple Jump, 2018; Oikocredit, 2019). It is also identified in the literature that FDI to local SMEs, by increased access to financial services, are an important contributor to domestic economic development. They provide increased employment opportunities that create new sources of income for local households (Tülüce & Dogan, 2014; OECD, 2012; Tambunan, 2008). This is one of the main reasons why I obtained data from the *DGGF* as they primarily finance SMEs. SDG Target 8.3, specifically, focusses on the role of SMEs in supporting decent job creation, by formalising employment, which potentially results in higher labour standards:

Promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial service.

Evaluating the impact of investments on these targets is not as straightforward as one might assume. *FMO* (2019) studied the principle of job quality and how this can be best measured. They identified that it is a complex but not impossible task to devise a common framework on job quality measurements. In their investments, they aim to influence pay and working conditions of local workers that are generally unskilled and vulnerable. *TJ* reportedly use impact indicators that illustrate the contribution to female employment and youth employment. *Oiko* reports similar indicators, evaluating their effect on the financial health of SMEs and both job creation and retention. Based on the investment data made available by *TJ*, as stated before, this research will evaluate their impact on female and youth employment. However, before diving into the data, I first discuss the relevant literature for this research and its discussion.

3. Literature Review

I described in the introduction that a number of different literatures will be reviewed in this research. This Chapter is divided into five Sections. They will assist the reader in understanding the context in which I argue academic research about *impact investment* should be placed. The first Section, *The History of Welfare and Economic Growth*, discusses the existing academic literature about *welfare* and *economic growth*. It will take the reader through historic developments in the relationship between these two concepts and ends with the conclusion that *wellbeing* should replace

[6] See Appendix B, P.73 for a breakdown of SDG 8 and its targets

welfare in academic literature. In the second Section I review the academic literature about FDI's relationship with employment, followed by its relationship with economic growth. As argued in the introduction, FDI is said to play a key role in the achievement of the UN SDGs, especially in developing countries (OECD, 2015). Developing countries are often limited by a lack of financial resources and human capital to develop their economy to a sophisticated level. These limitations could possibly be mitigated by *SII*. The third Section introduces the existing academic and policy- and practice-oriented research in the *SII* market. I continue in the fourth Section detailing the literature on SME finance, followed by the fifth Section, in which I present the hypotheses of this research.

3.1. The History of Welfare and Economic Growth

3.1.1. Pre – 20th century

Historically, economic growth was determined by the King's, or any type of ruler's wealth. However, I will not go that far back into history. Classical economic theory dictates the first arguments for a measure of a nation's yearly income for economic growth *(i.e. GDP*). In this economic thought, free markets are self-regulating, arguing that this measure also includes the social welfare of the nation as a whole. In 1776, Adam Smith made one of the most prominent contributions to economic theory, which is thought to be the foundation of classical economic thought. In his book, *The Wealth of Nations,* he introduced *The Invisible Hand*. Without government intervention, the market can, on its own, through self-interested behaviour, lead to a nation's highest level of social welfare. In the early 19th century, Thomas R. Malthus introduced the idea that population growth would surpass economic development and lead to an inefficient allocation of the planet's resources. This would give rise to famine and disease to parts of the population and thus, is detrimental to social welfare (Malthus, 1826). He suggested that government intervention could mitigate such market failures. These ideas led to the 20th century economic thinking by John M. Keynes. At the time, however, economists such as John S. Mill critiqued Malthus' proposed role of government. They believed that the government itself is too corrupt, as opposed to moral individual agents. John S. Mill was a supporter of *utilitarianism*, which was firstly formulated, by Jeremy Bentham, as the *greatest-happiness principle.* If an agent is given a choice between two or more actions, they will choose the action that provides them with the highest level of happiness (Bentham, 1789). This led to the development of the utilitarian social welfare function.

3.1.2. 20th Century

The social welfare function was introduced by Abram Bergson in 1938 in an article *'A Reformulation of Certain Aspects of Welfare Economics':*

$$\boldsymbol{W = W(U_{1,}, U_2, U_{3,}, \dots, U_{n,})}$$

Where W is social welfare, and $U_{1,}, U_2, U_{3,}, \dots, U_{n,}$ stand for the ordinal utility indices of multiple individuals in the population (Bergson, 1938) . To determine the utility indices for individuals there are explicit value judgements needed. However, these were not specified as Bergson argued that these should be obtained from the public itself. Thus, this model is dynamic, since it can be adapted through time with different value judgements. A problem one can imagine in this case is that looking at this from a micro-perspective, individuals are not homogenous and thus derive utility from different activities. Therefore, it should be useful to determine a set number of value judgements that are thought to be relevant for every individual, regardless of their individual preference. For example, one could say that the UN SDGs represent a specific set of values. If achieved, they could increase social welfare, according Bergson-Samuelson's model.

A revised social welfare function was introduced by John Rawls, a political philosopher. It is based on these two principles:

1. *Each person is to have an equal right to the most extensive total system of equal basic liberties compatible with a similar system of liberty for all*
2. *Social and economic inequalities are to be arranged so that they are both:*
    a. *To the greatest benefit of the least advantaged, consistent with the just savings principle, and*
    b. *Attached to offices and positions open to all under conditions of fair equality and opportunity (Rawls, 1971).*

The Rawlsian approach describes that the welfare of a society should be based on the prospects of the worst-off individual. It is also referred to the maximin criterion. This thought opened up a new perspective on social welfare and also resulted in a different optimal outcome. Interestingly, one should be able to recognize a commonality with the UN SDGs and this approach. Specifically, principle 2(a) of Rawls and the UN SDGs' pledge, to leave no one behind.

In 1920, Arthur Pigou argued that there is a divergence in marginal private interest and marginal social interest. In his thought, there is no incentive for an industrialist to cover the marginal social costs of their activities. These activities are described by the term, negative externalities. Such externalities range from environmental deterioration, crime, health damage, etc. He introduced a Pigouvian tax, which was further developed by William Baumol in 1972. The tax should work as an incentive for producers to develop solutions to minimize or even eradicate the negative social cost. In theory, this sounds like a valuable perspective on social welfare. In the current economic system, there exist, in most countries, excise duties for products that contain alcohol, tobacco and mineral oils (Belastingdienst, 2020). These are also meant as an incentive for producers to move to products that are less damaging for a person's health, and at the same time increases the prices of the products for consumers.

The 20th century has seen many developments regarding social welfare in economic models. The models discussed have attempted to account for social welfare in economic theory, primarily, on a micro-level. It is Simon Kuznets (1934), known for his impeccable contribution to measuring national income, that stated that economic welfare cannot, adequately, be measured if individual income distribution is unknown. In his own words: *"The welfare of a nation can, therefore, scarcely be inferred from a measurement of national income".* A valuable quote, coming from one of the founders of GDP measurement. He stressed that one should always keep in mind the difference between quantity and quality of growth, costs and returns, and to distinguish between short and long run achievements (Kuznets, 1962). Nonetheless, measures for GDP remained widely used both in academics and in policy, to measure and describe the economic prosperity of a population. In addition, Seers (1963) pointed out that the well-known neoclassical approach was too narrowly focused. He identified that this was reflected in scientific research about economic development, as these were limited to a specific set of underlying value judgements. He repeated in another paper that limited thinking about development and economic growth would not account for income inequality and unemployment. He emphasized that economic development and social progress are not always aligned (Seers, 1969).

3.1.3. 21st Century

It is only in the last 2 decades that the abovementioned message by Kuznets (1962) and the ideas of Seers (1963) have started to resonate through to new economic thinking. As described earlier, this is mainly due to the rising importance of global social and environmental issues, and their relevance to the wellbeing of the whole population. It has become a widespread belief that we need to look beyond GDP if we want to describe a population's wellbeing (Stiglitz, Sen, & Fitoussi, 2008; Coyle, 2011; McGregor & Pouw, 2016; United Nations, 2015). GDP has over the last couple of years received a lot of criticism, specifically from Joseph Stiglitz. Together with other researchers he introduced the Green GDP, which should entail sustainable measures of economic growth, savings and wealth (Stiglitz, Sen, & Fitoussi, 2008). However, Stiglitz himself is critical about the Green GDP as it does not measure sustainable outcomes by itself. It only adds a cost for the damage and depletion of environmental resources to GDP. Note here the similarity with the Pigouvian Tax. Many studies, in recent years, have made it their goal to search for alternative measures for economic growth, that also entail the economy's relation to human and ecological wellbeing. Measures that have been proposed by academics are the Genuine Progress Indicator (GPI), Human Development Index (HDI), Life Satisfaction, Ecological Footprint and the Gini Coefficient (Brennan, 2008; Wilkinson & Pickett, 2009; Kubiszweksi, et al., 2013). Overall, findings do conclude a better approximation of economic growth, entailing its socio-economic and environmental implications. There is, however, not yet, a unified measure that incorporates socio-economic and environmental factors that could conceptualise a *wellbeing economy*. One can argue that an economy consists of too many different determinants and thus its implications to human and ecological wellbeing cannot be summarized in a single variable.

McGregor and Pouw (2016) made their contribution towards conceptualising a wellbeing economy, by focussing on the relationship between economic growth and human wellbeing. They propose that the problem is more of a fundamental kind, looking beyond the homo economicus and a rational economic agent. In addition, they question the meaning of *welfare* in neoclassical micro-economic theory. Even though, *welfare* has long been present in economic thinking, it does not refer to human and ecological wellbeing. Thus, calling for a shift from looking at *welfare* to *wellbeing.* One can imagine that defining any kind of *wellbeing,* whether economic, human or ecological, is rather subjective, based on a person's value judgements. It would be close to impossible to come up with a model that accounts for every person's individual wellbeing. Philosophers have been pessimistic about the ability to come up with a single measure for *wellbeing* (van der Deijl, 2017). The goal of this paper is not to come up with a single measure for *wellbeing* and thus a *wellbeing economy.* However, it will, on the basis of recent developments in economic thinking, evaluate impact measures for employment that may contribute to the conceptualisation thereof.

Raworth (2012) recently developed a diagram for economic thinking, referred to as *Doughnut Economics*[7], in a paper, *A safe and just space for humanity,* published by Oxfam. She further elaborated on the Doughnut diagram in her book *Doughnut Economics: Seven ways to Think Like a 21st-Century Economist.* It is meant to oppose the traditional thought of growth economics, that used GDP as its main indicator. The diagram illustrates a new perspective, by including socio-economic and environmental determinants to its model to serve the needs of the 21st century. The *Doughnut* consists of multiple layers. On the inner circle, there is the social foundation (derived from the UN SDGs) that entails 12 elements, as shown in **Table 4**:

The Social Foundation of the Doughnut Economy	
1. Education	2. Housing
3. Income & Work	4. Networks
5. Peace & Justice	6. Energy
7. Political Voice	8. Water
9. Social Equity	10. Food
11. Gender Equality	12. Health

Table 4: 12 elements of the Social Foundation of a Doughnut Economy

These elements represent the centre whole of the doughnut, which describes the possible shortcomings of the economy, such as people's lack of access to education, employment and clean energy, among others. The outer circle represents the ecological ceiling, consisting of 9 planetary boundaries, as shown **in Table 5.**

The Planetary Boundaries of the Doughnut Economy	
1. Climate Change	2. Land Conversion
3. Ocean Acidification	4. Biodiversity Loss
5. Chemical Pollution	6. Air Pollution
7. Nitrogen & Phosphorus loading	8. Ozone Layer Depletion
9. Freshwater withdrawals	

Table 5: 9 planetary boundaries in Doughnut economics

The boundaries are, logically, not supposed to be overshot by economic activity. *The Safe and Just Space for Humanity* is argued to be the doughnut itself. If the world finds itself in a position where all 12 social foundations are met, without surpassing the ecological ceiling, then we could, arguably, begin to describe a *wellbeing economy* (Raworth, 2018).

Now that we have explored previous literature about *welfare* and *economic growth,* the reader should be able to understand the developments that have led to the use of the term *wellbeing* instead of *welfare*. To further contribute to the conceptualisation of a *wellbeing economy* and to move closer to the topic of our statistical analysis, I review the literature on the impact of FDI on a host country, through *employment-effects* and *economic growth-effects*, in the next Section.

[7] See Appendix A, Figure A1, on P.68 for a Diagram of the Doughnut Economy

3.2. The Impact of Foreign Direct Investment

3.2.1. Foreign Direct Investment and Employment

It has been a widespread debate in academics what kind of effect FDI has on a host country. Many papers argue that there are positive externalities to be enjoyed. However, when it comes to socio-economic and environmental factors, such as local resource allocation, employment and the overall wellbeing of a host country, academic theories predict FDI to be detrimental (Brecher & Diaz-Alejandro, 1977). One of the main issues identified in previous papers is to quantify both the direct and the indirect effects of FDI. Furthermore, researchers and practitioners also indicate the need to recognize the counterfactual when measuring impact. This means that one should consider what would have happened, without the presence of FDI (Lall, 1995). One can imagine that is a question that is close to impossible to quantify due to the many assumptions that need to be made. Nonetheless, a number of papers have attempted to find their way around these limitations to determine the relationship between FDI and employment.

In the literature, most papers focus on the relationship between factors of employment and FDI through investment activities of multinational corporations (MNCs). It is a common understanding that MNCs are a significant driver of FDI in international investment. They can set up a foreign affiliate, known as greenfield investment, or buy an existing local firm, known as brownfield investment. This is mostly true in developed countries with a specific level of economic and market sophistication. However, in developing countries this could be less of a significant effect due to different geographic and economic conditions. Lall (1995) suggests that host countries should have a combination of policies in place to enhance the positive externalities. Examples of such policies are tax incentives, performance requirements, local participation, export incentives, infrastructure, etc. These policies are suggested to attract more FDI and at the same time protect local interests from foreign influence and control. For example, greenfield investment may cause a crowding-out of the local workforce, if the MNCs don't accommodate employment for the local workforce.

However, it is a common consensus that MNCs are mostly attracted to developing countries due to the relatively lower wages and less restrictive labour standards than in their home country. This often leads to the argument that MNCs exploit the local workforce of these countries by reallocating their low-skilled labour-intensive output to developing countries (Blomström, Fors, & Lipsey, 1997; Zhao, 1998). There exists earlier research that focused on the relationship between labour income and international trade and investment. Papers by Bhagwati and Srinivasan (1983) and Magee (1973) investigate how wage differentials are affected by market distortions. While others analysed whether labour unions protect local employment and their wages. (Mezzetti & Dinopoulos, 1991; Driffill & van der Ploeg, 1993). Labour unions should, in effect, set decent labour standards and protect their labour rights. Zhao (1998) identified that labour unions are not equally concerned about employment and wages. In his paper, he found evidence that FDI reduces employment and the competitive wage in a non-unionized sector. This effect is largely reduced if there is an industry-wide labour union.

Even though there is common understanding that MNCs enjoy the low labour standards and lower relative wages, Blomström and Kokko (2003) also argue that MNCs in some cases demand high skilled labour in developing countries. Due to this demand, MNCs are often involved in both financial and non-financial support in the host country, to help realise their ability to meet that demand. This can be exemplified by incentivising local governments to invest in higher education, through encouraging students to pursue tertiary education, in addition to primary and secondary education. MNCs often sponsor formal education programs, not limited to their own employees but also assist in the development of sophisticated universities and other educational institutions (UNCTAD, 1999). However, in more recent papers, it is argued that the positive contribution of FDI is conditional on the level of human capital of the host country. This is evidently troublesome for developing countries that do not meet this requirement. As was stated earlier, this positive effect of FDI is primarily identified in developed countries. In light of this conditionality, researchers identified that the relationship between FDI and employment is not, by nature, linear. If a host country has a relatively high level of human capital, it could attract more FDI, which could result in further enhancing the level of human capital (Borensztein, De Gregorio, & Lee, 1998; Li & Liu, 2005). Therefore, the relationship is rather complex and could be proven as cyclic causation. Furthermore, there are papers that find positive effects of FDI on domestic firms, e.g. SMEs. (Javorcik, 2004; Görg & Greenway, 2004). This spill-over could further develop into domestic economic growth, which will be further discussed in the next Sub-Section.

3.2.2. Foreign Direct Investment and Economic Growth

On the basis of earlier research, I argued in the previous Section that there is a complex relationship between FDI and employment due to a possible cyclic causation. This relationship could be similarly cyclic when discussing the sophistication of economic conditions. One could argue that a country with relatively high economic growth, attracts more FDI, which in turn positively affects economic growth. Furthermore, it could be stated that if employment conditions are well, this could positively affect a country's economic growth. Numerous papers have debated the contribution of FDI on a host country's economic growth. Noteworthy is that in the literature, a measure of GDP is most commonly used to illustrate economic growth. Considering our review in Section 3.1, that is important to keep in mind for the continuation of this Section of the literature review.

Evidently, there is some overlap between FDI's relationship between employment and its relationship with economic growth. Similar to the employment effects, FDI is believed to contribute to a host country's economic growth due to the variety of positive externalities it brings forward. A prominent reason is that it provides additional capital into a country's, previously limited, national income. This results in the expectation that the economy will subsequently benefit from knowledge-, technology-, and productivity spill-overs. Such spill-overs may lead to a more efficient resource allocation and factor productivity and a more sophisticated workforce. These may take place through trainings, imitation, competition, or other linkages between multinationals and domestic firms (Kinoshita, 2001). I previously discussed that the positive effect of FDI on employment is conditional on specific economic conditions, such as human capital. Subsequently, I argued that this could also be the case for its relationship with economic growth. Li & Liu (2005) argue that the relationship between FDI and economic growth is not exogenous and test for endogeneity by introducing multiple interaction terms with FDI. They find a positive significant interaction effect with both human capital and educational attainment and negative significant effect with the technology gap on economic growth. This finding contributes to the theory that FDI is attracted to host countries with a sufficient level of human capital and technology capacity.

In an earlier paper, Borensztein et al. (1998) had already found evidence that FDI's positive effect was conditional on the level of human capital in the host country. Thus, if both the knowledge- and the technology gap are too large, the positive effect of FDI on economic growth is reduced. In addition, Hermes & Lensink (2003) find that the sophistication of a host country's financial system is a determinant for FDI and subsequently a condition for its positive effect on economic growth. A number of other studies also found a liberalized market and economic stability were a condition for there to be a positive correlation between FDI and economic growth. That is mainly due to the fact that this kind of environment would enhance the knowledge- and technology spill-overs, and allows competition while limiting market distortions (Bhagwati J. , 1978; Balasubramanyam, Salisu, & Sapsford, 1996; Bengoa & Sanchez-Robles, 2003). To summarize these findings, host country characteristics are prominent determinants, not only of the impact of FDI on economic growth, but also their ability to attract FDI in the first place.

As previously stated, there are academic theories that predict FDI to be damaging to local resource allocation, employment and the overall wellbeing of the host country. On the basis of previous literature, one cannot conclude that this is solely due to the fact that they do not meet the relevant threshold. In the contrary, it could also be dependent on the incentives of the FDI source. It is believed that FDI through *SII* is more able to mitigate such damages to socio-economic and environmental factors and as a result economic growth. The following Section will review the existing literature on *SII*.

3.3. Landscape of Research on Social Impact Investment

3.3.1. Academic Research in the SII market

Daggers & Nicholls (2016) conducted a survey analysis spread through different academic institutions and found that there are some academics that focus on the *SII* market. Most papers that they found focus on *SII* in Western countries. There are very limited to no academic papers that have a geographical focus on developing countries. This research contributes to the existing literature by analysing data on *SII* in mostly developing countries. One of the main issues identified in the existing literature is the terminology in the *SII* market. Because the academic field is relatively new, researchers adopt vocabulary to the benefit of their own paper. As previously said, Daggers & Nicholls (2016) clarify there is a distinction to be made between *social investment* and *impact investment*. Most of the existing literature in social impact investment does not yet recognize this distinction. As noted in Chapter 2, I will continue to use the term *impact investment* (GIIN, 2019).

There are a number of topics, in which *SII* research is primarily present. Most papers relate to measuring the impact of microfinance (Weber H. , 2002; Battilana & Dorado, 2010; Montgomery & Weiss, 2011; Weber O. , 2013; Banerjee, Karlan, & Zinman, 2015), followed by papers evaluating ESGs and RI (Harold, Spitzer, & Emerson, 2007; Lehtonen, 2013).[8] Microfinance has been argued to be a successful tool to alleviate poverty through providing small loans to financially constrained entrepreneurs and households. H. Weber (2002) argued that microfinance positively affects the liberalisation of the financial sector allowing capital-constraint countries to participate in global trade activities. In the 1990s, when demand for credit by poor countries increased rapidly,

[8] A full list of topics identified by Daggers & Nicholls (2016), see Appendix A, Table A3, P.69

commercialized microfinance institutions (MFIs) were established, working to both meet social objectives and financial return. (Battilana & Dorado, 2010). There are continuous discussions about the impact of MFIs, both positive and negative.

A paper by Montgomery and Weiss (2011) investigated whether MFIs could contribute to the achievement of the UN Millennium Development Goals (MDGs), the SDGs' predecessors. They found that in rural areas, in Pakistan, an increased access to microcredit led to better health and education for borrowers and their children. In contrast, van Rooyen, Stewart and De Wet (2012) found that microfinance, in Sub-Saharan Africa, can sometimes reduce the level of children's education and disempower women. These conflicting results may indicate that it is also a matter of location that plays a large role. This has led to an increasing debate about how impact in microfinance can be, or better yet, should be measured. Furthermore, O. Weber (2013) suggested that the objectives of MFIs vary, which could also affect its impact. He argues that MFIs' objectives go beyond alleviating poverty and range from supporting local SMEs, to local economic development, fostering individual development and empowerment. This does not, however, exclude the possibility that some MFIs' objectives can overlap. This is, particularly, evident when we look at the implication that to measure impact, we should not only look at output measurement but also outcome measurement. As an example, an output measure for SME financing, would be the number of loans provided to SMEs, increasing local financial resources. However, more interesting is the outcomes of providing more loans. For example, increasing employment opportunities, which, logically, increases the income of households and could thus alleviate poverty. They are two very distinct measures and are widely discussed in policy- and practice-oriented research. I will elaborate on this in the next Sub-Section.

3.3.2. Policy- and Practice-Oriented research in the SII Market

The amount of policy- and practice-oriented research is larger than academic research. Since the development of the *SII* market, practitioners have gathered in working groups and professional networks to conduct research on the developments of this particular market. Most of the research conducted and reports published are based on the desire to develop a unified framework to measure the impact of their investments and their alignment to SDGs. In addition, this research is primarily conducted with firm-level data, not country-level data. This is mainly due to the fact that one cannot simply extrapolate output and outcomes of firm-level investment data of one investor to the host country, as a whole. In this Sub-Section, I first discuss SDG alignment, followed by impact measurement methodologies, and finally the importance of context in impact measurement. This research argues that the UN SDGs could help contribute to devising a unified framework to measure and report impact investment output and outcomes.

3.3.2.1. <u>SDG alignment in Impact Performance, Measurement and Management</u>

In the past years, there have been a number of global and national initiatives between organisations that have the desire to further develop the *SII* market. In Section 2.2, I briefly introduced the GIIN. They aim to accelerate the market's development and sophistication, through facilitating knowledge transfers between impact investors and building the evidence base for the *SII* market. They conduct research on impact performance, measurement and management practice to establish the future of the *SII* market and reshape financial markets. To establish the future of these markets, they devise a roadmap that should assist in the development of more inclusive and sustainable financial markets, where impact investing should play a leading role (Bouri, Mudaliar, Schiff, Bass, & Hannah, 2018). On impact performance, they present new approaches to compare impact results of investments in a specific sector, such as clean energy or housing. From their suggestions, it should be evident that context is key to interpret impact results reliably (Bass, Nova, & Sunderji, 2019). GIIN (2019) published a report on the current state of impact measurement and practice by surveying 278 impact investors. In their report, they identified 17 impact targets, all of which can be related to the UN SDGs. For example, the majority of impact investors identified *employment* as their primary impact category and *financial inclusion* as third, relating to SDG 1 and 8. Diversity and inclusion relate to SDG 5. Furthermore, health and education relate to SDG 3 & 4, respectively.[9]

There exist initiatives that aim to support the development of the *SII* market by seeking alignments with the SDGs. The Stockholm declaration was founded by leading players in the global investment community, committing to using the UN SDGs as a central framework in their investment activities (Stockholm Declaration, 2017). In 2016, the Dutch SDG investing (SDGI) initiative was established and resulted in the Dutch SDGI agenda, which was signed by 18 financial institutions, 3 enabling networks and 2 facilitators.[10] The goal of the initiative is to stimulate a common narrative, converging, coordinating and collaborating between key players in the market and other relevant stakeholders (SDGI, 2016). Areas of focus included making SDGI more common place among market players, needing greater convergence of capital, devising data standards and putting a supportive regulatory environment in place. The initiative invited the Dutch government and the Dutch Central Bank (DNB) to support their agenda and pursue the recommendations made to the financial sector, government and regulators (SDGI Signatories, 2016). As a result, in 2017, DNB published a report, co-authored by multiple SDGI signatories, describing existing SDG impact indicators established by the UN, and redefining them to make them relevant and usable for investors.[11] The report is a first step into realising a closer alignment between investment decisions and the UN SDGs.

In September 2019, Algemene Pensioen Groep N.V. (APG) and Pensioenfonds voor de Gezondheid, Geestelijke en Maatschappelijke belangen (PGGM) developed a platform that uses artificial intelligence to track and evaluate sustainable development investments (SDIs)[12]. In collaboration with a group of international investors, they defined SDIs and analysed the measurability and investability of specific SDGs. The ultimate goal is to track their impact and use their results for future investment decisions. In their report, they categorize each SDG in 3 characteristics; not investable, investable and a potential for acknowledged transformational leader (ATL). With ATL, they illustrate SDGs for which there exist companies that could provide leadership in the issues related to that SDG (Rust, 2017). For the purpose of this research, I zoom into their results for SDG 8 **in Table 6**.[13] Interestingly, they have not concluded that SDG 8 is either

[9] See Appendix A, Table A2 P.69 for the list of target impact categories
[10] See Appendix A, Table A5, P. 70 for a full list of all signatories
[11] The SDG impact indicators established by the UN are primarily useful for governments, not investors (De Nederlandsche Bank, 2017). See Appendix A, Table A6, P. 71 for a list of all authors of the SDG Impact Report
[12] Social Development Investments is a term used to describe investments where financial risk and return requirements are met and the recipients products, services or overall objectives contribute to realising the UN SDGs (PGGM, 2019).
[13] See Appendix A, Table A4, P.70 to get a full overview of their results for each SDG

investable or not investable and only describe it as a potential ATL. The reason is that they only find that 1 out of the 12 SDG 8 targets could be investable through commonality with SDG 12, and 3 out of 12 are potential ATLs:

Results SDG 8 – SDI Taxonomy	
8.4 – Resource Efficiency in consumption and production	See SDG 12
8.5 – Achieve full and productive employment	Candidate ATL
8.7 – Elimination of worst forms of child labour and eradicate forced labour	Candidate ATL
8.8 – Protect labour rights and promote safe working environments, including migrant workers.	Candidate ATL

Table 6: Summary of results SDG 8. Source: (APG & PGGM, 2017)

One can observe from **Table 6**, that our focus target 8.3 is neither specified to be investable nor a potential ATL. By analysing the methodology used by APG & PGGM, one can interpret this as that SDG 8.3 does not meet the financial risk and return requirements in their SDI model. In contrast, *FMO*, *TJ* and *Oiko* have indicated that they have investments in their portfolio that approach SDG 8, beyond the targets specified by APG & PGGM. Evidently, they are different type of investors and it makes sense that they do not find the same results. Mainly due to the fact that they are likely to differ in their financial risk and return requirements. APG & PGGM are both asset managers and pension fund managers, and thus they are responsible for the pensions of approximately 7.5 million Dutch workers (APG, 2020; PGGM, 2020). One can imagine that, due to this responsibility, their financial risk and return requirements are higher than other kinds of impact investors. They need to be responsible investors, not only to their social cause but more importantly to their clients. I do not mean to say that other impact investors take too much risk and are not responsible in their investment decisions. I do, however, argue that they have the capacity to take on riskier investments in their portfolio. This could be a reason for them to invest in other targets, such as SDG target 8.3.

3.3.2.2. Methodologies of Impact Measurement

As described in the Sub-Section 3.3.1, I argued that it is important to not only look at the investment output, but also at the outcome of the investment. In 2014, *FMO* published their impact model, which was developed by Steward Redqueen; a prominent consultancy firm in the field of impact measurement on local economies for DFIs. It identifies both direct investment effects through end-beneficiaries and indirect investment effects through financial intermediaries that re-invest *FMO*'s money locally. Investment output (direct impact) is derived from data collected by *FMO'*s clients, while investment outcomes (indirect impact) are more difficult to quantify. In 2019, Jane Ambachtsheer, Global Head of Sustainability for BNP Paribas Asset Management, stated that "*to date, there is no harmonised framework for measuring or reporting impact investment outcome*s". This is mainly because investment outcomes are difficult to trace. They can be tracked through the linkages between sectors and their interdependencies, by following the flow of products and money in an economy (FMO, 2019). Therefore, it is crucial to distinguish output measures from outcome measures.

In practice, a number of measurements indicators have been proposed to measure impact in the *SII* market. There exists a database, the IRIS Catalogue, which develops and gathers large numbers of indicators to be implemented by investors (GIIN, 2020). More specifically, for the measurement of employment in target 8.3., indicators such a youth employment rate both in the formal and informal sector are proposed. Mainly because the quality of jobs in these two sectors differ greatly. In the formal sector, employment is regulated and thus should be more aligned with specific labour standards (Sustainable Development Solutions Network, 2020). In collaboration with European Development Finance Institutions (EDFIs), *FMO* (2019) reported the importance of promoting not just quantity of jobs but also quality of jobs. The report recognises that job quality is defined by multiple factors such as real wages, intrinsic characteristics of work, health and safety, work-life balance, etc. In addition, the International Finance Corporation (IFC) (2012) highlights that a sufficiently high level of labour standards may reduce commitment and retention and increase their efficiency and productivity. This should benefit the company and country as a whole.

3.3.2.3. Importance of Context in Impact Measurement

It has been stated multiple times that context is key in measuring impact, relating to specific countries and/or sectors. Therefore, it is important to identify to what extent impact investors are active in different parts of the world. Monteiro (2016) highlighted that *"Sub-Saharan Africa is the region where the highest portion of impact investors plans to increase their allocations, followed closely by East and South East Asia"*. In figures, GIIN (2019) reported that Sub-Saharan Africa accounts for 14% of total *assets under management* (AUM) in their survey to global impact investors. While 44% of respondents indicated they allocate assets to Sub-Saharan Africa. To put this in perspective, only the USA & Canada account for more AUM, namely 28%, while 47% of respondents indicated they invest there. Only Latin-America also accounts for 14% of AUM, while only 34% of investors indicated they are active in that region. It is identified by EDFIs that investing in the poorest countries also brings in a number of limitations. One is that the majority of employment is informal, which makes it hard to collect data. In addition, since the formal sector is a minority, one could interpret this as an indication that *International Labour Organisation* (ILO) standards are not followed by convention (FMO, 2019). Characteristics of the informal sector are long working hours, low productivity, low and unstable wages. However, this should be all the more reason to invest in these regions to help domestic firms join the formal sector through capital inflow and informing them of better business practices and promote sophisticated labour standards.

Interestingly, Sub-Saharan Africa mainly attracts investors that target smaller returns on their investment and use debt-type finance. Overall, the risks in Sub-Saharan Africa are also higher than, for example in South East Asia, where there is more equity-type finance and higher return targets (The Impact Programme, 2015). This is a peculiar trend, since, intuitively, one would expect that investors that target higher risk investments also target higher returns. These figures suggest that the Internal Rate of Return (IRR) of these investments does not only depend on risk alone. As previously exemplified with PGGM & APG vs. *FMO*, *TJ* and *Oiko*, it may depend on investor characteristics, such as their overall investment agenda, the diversity of their investment-portfolio and geographic focus. Monteiro (2016) explains that the challenge for developing countries is to channel investment towards implementing the SDGs. In addition to many other investors involved in the *SII* market, he argues that impact investors are able to help with such challenges, by focussing on markets that have limited access to financial resources, such as markets consisting of SMEs. This will be further explored in the next Section.

3.4. Review of SME Financing literature

Increasing SMEs' access to capital can positively impact employment objectives in developing countries. In other words, it could be a useful tool to achieve SDG target 8.3. Tülüce and Dogan (2014) argue that domestic firms, primarily SMEs, can benefit from FDI through improvements in the quality of the labour force and infrastructure and increases in research & development activities. In addition, FDI inflow also represents an opportunity for SMEs' role in local economic development, through increased competition in the market (OECD, 2012). As a result, SMEs are often identified as a contributor to alleviating poverty, through wealth and job creation in host countries. Note that wealth and job creation are an output measure and alleviating poverty is an outcome measure. Tambunan (2008) states that SMEs largely generate domestic employment, in Indonesia, providing livelihood for more than 90% of the local labour force, including women and youngsters. This generates sources of income for different population groups and households. However, economic and political conditions can be an impediment to the effect of SMEs on economic development, especially in developing countries. This makes sense, as such conditions were previously identified as an impediment for all FDI. In addition, Etuk, Etuk and Baghebo (2014) argue that in developing countries, such as Nigeria, local governments tend to overlook the needs of SMEs. This could be another reason why FDI is important to meet the needs of SMEs, and help local governments support them. Nasr & Rostom (2013) had identified the same challenge in Northern Africa and the Middle East. Without FDI, liberalizing reforms in regional policies need to be effectively enforced for SMEs to have a sustained role in job creation, taking both quantity and quality of jobs into account (Al-yahya & Airey, 2013).

3.5. Formation of the hypotheses

On the basis of the insights given by the existing literatures on FDI, employment, economic growth and trends in the *SII* market, I move on to developing hypotheses that should help to answer the research question. Due to the fact that I conduct a case-study, using data from the *DGGF*, I realise that the data pertains to firm-level data. In other words, the hypotheses and the results cannot simply be linked to the whole country in which the SMEs were active. The results are specific to the SMEs in *DGGF's* portfolio and will be interpreted as such. It is, however, relevant to use certain country-specific characteristics as control variables, since this was described to play a role in the impact of foreign investments. The dataset includes data on three employment indicators, female- and youth employment (ages 18 – 24 and 25 – 35) and I make a clear distinction between these three in my data analysis. For each indicator, I design its own dataset. This is further elaborated on in Chapter 4. The first hypothesis is based on the notion that FDI can bring a positive impact on employment through SME financing. I argue that this is evident in the capital invested by *DGGF* and its financial intermediaries. Note that in all hypotheses, *employment* refers to *Female Employment, Youth Employment (18 – 24) and Youth Employment (25 – 35).*

Therefore, the first hypothesis that I will test, for each of the three employment indicators, is as follows:

H1. Providing capital to SMEs has a positive impact on employment change.

As described in the literature review, there are often differences between countries and sectors in data analysis of investments and its effect on local indicators. In the dataset, the country and sector of their primary operations are specified, which allows us to test whether there are differences, in this data, between both countries and sectors in the change in employment in all three indicators. Therefore, I present the following hypotheses:

H2: The employment change in SMEs resulting from the investment is significantly different across the countries of primary operations.

H3: The employment change in SMEs resulting from the investment is significantly different across the sectors of primary operations.

I decided not to pursue these hypotheses for total employment, because I wanted to dive into these specific demographics of female and youth employment. It should be noted that a change in total employment is, of course, invaluable and also a great impact on the SME. However, the argument that I made earlier is that it is important to look beyond general employment and unemployment levels. Total employment will be considered in the different datasets but its relationship with the investment is not specifically tested. In the following chapter, I describe the data sources, datasets and the statistical methodology used to test the above hypotheses.

4. Data & Methodology

Collecting data in the *SII* market continues to be a challenge for most researchers, which is one of the reasons that there are still many knowledge gaps in this field. This is true, not only for academic researchers, but also for policy- and practice-oriented researchers. We need data on both financial indicators and social impact indicators in this market. Due to the novelty of this topic, there is no country-level data available on the *SII* market. The market is, simply, not matured sufficiently for countries to have enough data on these investments and social impact indicators. In the current landscape of research in the *SII* market, as described in the literature review, it is more valuable to utilise investment data from impact investors and conduct a case-study analysis. By doing this, I do not only contribute to the academic landscape of research in this field, but more importantly to the understanding of social impact of those investors. The challenge, of course, is to find an appropriate case study. It is for that reason that I approached *FMO, TJ* and *Oiko,* to explore whether I could use data from their SME portfolio, in addition to the qualitative insights they provided. All three were eager to help with quantitative data, but also stressed the complications that arise in social impact performance data analysis. One main limitation was the quality of their SME portfolio data, not having collected relevant data pertaining to social impact indicators, more specifically employment indicators. With the aim to have data on such indicators, I was able to retrieve investment data, through *TJ,* from the *DGGF*, whose primary objective is financing SMEs. Since I also want to include certain country-specific control variables, I also retrieve data from the *World Bank Database (WBD)* and the *ILO.*

Using these different data sources is not, as has been described earlier, self-evident. This is mainly since one source is firm-level data, while the other is country-level data. In addition, one is cross-Section, while the other is time-series. In the following two Sections, I provide a detailed description of the data sources and the treatments I performed, in order to combine them in a statistically accurate manner. This will ensure that the reader, but also prospective researchers in this field, have a comprehensive understanding of how the data is utilised and what kind of limitations need to be accounted for.

4.1. Dutch Good Growth Fund Data

The primary data source of this research is the *Dutch Good Growth Fund,* provided by impact investor, *Triple Jump.* This fund was launched in 2014 and specifically focuses on financing SMEs, largely in emerging markets and developing countries. *TJ* manages the investments of this fund on behalf of the Dutch Ministry of Foreign Affairs (Rijksdienst voor Ondernemend Nederland, 2020). It is reported that they are mostly active in *Sub-Saharan Africa* (37%), *Middle East and North Africa* (16%) and *Central Asia* (12%) (Triple Jump, 2019). The main goals of these investments are to ensure living wages and job security in those regions. In particular, to serve the population groups for which those two goals are most challenging to achieve, i.e. women and youth (Triple Jump, 2018). Since their establishment until the end of 2019, it has invested in a total of 7162 SMEs, financed through 42 different financial intermediaries across 41 countries in 9 different world regions. The main limitation of this data is that not all SMEs have complete data on all the indicators that are provided, specifically relating to the financial performance and employment changes since the investment. In the next Sub-Section, I describe the initial dataset and introduce all its limitations.

4.1.1. Description of Initial DGGF Dataset

As previously described, the dataset consists of cross-Sectional firm-level data from the *DGGF's* investments through the years 2014 to 2019. Most investments are concentrated from 2017 – 2019, as the fund has grown over the years. All SMEs have a specified entry date, and if applicable, exit date, which allows to determine the timespan to which the data pertains. In addition, countries and sectors of primary operations are specified for each SME, allowing to make distinctions between these two groups in the dataset, *Country* and *PrimarySector,* respectively. Only a very small number of SMEs are also active in other countries or sectors. For simplicity, this research disregards that specification. I do, however, add the variable *Region* to indicate in what world region the SMEs' primary operations are situated. The defined regions are based on the methodology devised by the UN and the World Bank (United Nations Statistics Division, 1999). The 9 regions specified, at this stage, are *Europe, Southern America, Central America, Caribbean, South Asia, South-East Asia, East Asia, Sub-Saharan Africa,* and *the Middle East*. The variable *PrimarySector,* initially, had long specifications for each sector. For simplicity, these specifications are shortened, which results into 20 sectors, including the specification where it is unknown[14]. Furthermore, as stated earlier, all capital is invested through several financial intermediaries, and with different kinds of investment instruments. The type of financial intermediary and investment instrument used is defined per SME. The variable *FundCategory* identifies the types of financial intermediaries, which can be specified as a *financial institution, pioneering fund, high impact, private equity* and *mezzanine finance.* Finally, the variable *InvestmentInstrument* categorises whether the investment was either debt, equity or both.

All financial indicators are expressed in US Dollars-$. There is monetary data on capital invested, both by the financial intermediary as a whole, and the portion by the *DGGF,*

[14] See Appendix A, Table A7, P.71 for a list of all sector definitions

TotalCapitalInvested and *CapitalInvested_DGGF*. This distinction is made since the total capital invested by the financial intermediary is sometimes higher than what was invested by the *DGGF*. The main explanatory variables for our first hypothesis are derived from these variables. In addition, there is data on the financial performance of the SMEs before entry and at the end of 2019, or if applicable when exited the portfolio, illustrated by revenue and profit indicators; *PriorRevenue, NewRevenue*, *PriorProfit* and *NewProfit.* These may be used as control variables, as the financial performance of the SME may affect their capacity to hire new employees. It should be noted that these figures for SMEs, especially those that are in the starting up phase of their life cycle, can be volatile. This should be taken into account when performing the statistical tests.

Most importantly, the *DGGF* collects data on total employment, female employment and youth employment (18 – 24 and 25 – 35), both prior to the investment and at the end of 2019 or if applicable, when exited the portfolio. *TJ* defines employment as "*Paid, working 8 or more hours per day for the company, excluding seasonal and temporary employees (this should include the owner(s) if they work for the company)"*. These variables are specified as follows: for total employment, *PriorEmployment* and *NewEmployment,* for female employment, *PriorEmployment_F* and *NewEmployment_F,* and for youth employment, *PriorEmployment_Y18_24, NewEmployment_Y18_24* and *PriorEmployment_Y25-35,* and *NewEmployment_Y25-35.* From these, I derive the dependent variables to test our three hypotheses. In addition, the variables denoted with "*Prior"* can be utilised as a lag control variable. The variables for total employment could be valuable to use as a control variable. Furthermore, the dataset determines whether SMEs can be characterised as a *FemaleSME*[15], based on the definition of female-owned enterprises from the *IFC.* This is a dummy variable, equal to one if meeting the definition requirements, and zero if it does not. In that same theory, *YouthSME*, is a dummy variable, indicating whether an SME is youth-owned or not. Both of these dummy variables allow for potential tests for differences in the respective employment indicators between SMEs that were previously defined as female- or youth-owned and those that were not. There is also data that, if applicable, categorizes the type of training SMEs have received. In addition, there is data on whether knowledge transfers were deemed beneficial to the SME. Although it would be interesting to further dive into the impact of non-financial aid, this goes beyond the scope of this research and thus is disregarded in the hypotheses testing. This could be an interesting perspective for future academic research.

As I previously described, data collection for impact investors is not self-evident, since not all investees share the data that investors wish to collect, in order to assess their social impact. This is also evident in the initial dataset provided and thus before diving into descriptive statistics, I need to account for all the incomplete datapoints. Most important, I need to ensure that there are sufficient datapoints for each of the dependent variables, the employment indicators, and the main explanatory variables, the financial indicators. A crucial observation is that there are SMEs that have valuable datapoints on female employment yet have no reported datapoints on youth employment, or vice versa. This could be due to the fact they do not report on the latter as they do not have youth employment. However, this cannot be determined from the dataset or through *TJ*. It is for that reason that I decide to design three

[15] *"An enterprise qualifies as a woman-owned enterprise if it meets the following criteria:
(A) ≥ 51% owned by woman/women; OR(B) ≥ 20% owned by woman/women; AND (i) has ≥ 1 woman as CEO/COO/President/Vice President; AND (ii) has ≥ 30% of the board of directors composed of women, where a board exists."* (IFC, 2020)

distinct datasets per female- and youth employment (18 – 24 and 25 – 35). This will ensure that when conducting treatments for missing datapoints, I derive the most complete datasets for each indicator. Note that each dataset will receive a similar treatment to account for the missing datapoints, unless specified otherwise.

In addition to a large number of missing datapoints, I previously recognised that the data is not annualised. Each individual SME has a unique reported time to which their datapoints refer. Some SMEs have only been in the portfolio for one year and others five to six years, which could ultimately affect their ability to hire new employees. This also needs to be taken into account. Furthermore, some variables have highly skewed data, which needs to be accounted for by transforming them into natural logarithms to result in a more standardised distribution. The treatments performed and additional limitations that arise are discussed in the next Sub-Section[16].

4.1.2. Transformation of the initial dataset

4.1.2.1. Time Dimension in the Dataset

The data does not provide an annualised overview of the variables. It entails datapoints from two points in time, the first being prior to the entry date, and the second, if applicable, the exit date. Otherwise, the second is recorded at the end of 2019. Given this, I derived a variable *TimeinPortfolio* that illustrates the number of months that the SME is in the portfolio. I decided to use number of months as a unit of measurement instead of years because an SME may enter in January 2015 or December 2015, which is almost a year's difference that would be disregarded. Due to skewedness, this variable is standardized through transforming it into a natural logarithm[17]. In addition, a dummy variable, *ExitPortfolio,* is added, describing whether the SME exited the portfolio, equal to 1 if it exited, and equal to 0 if it is still in the portfolio. An SME exits the portfolio in the event of a full repayment of the loan or repurchase of stock. Only in a handful of cases does it indicate that an SME has gone out of business and the loan is written-off. Therefore, I do not explicitly make a distinction between these two reasons for exiting the portfolio. It may be interesting to test whether SMEs that exited the portfolio have made a better contribution to the employment objectives, in contrast to those that are still in the portfolio. This could be true under the assumption that SMEs that did not exit the portfolio are still in the process of growing and thus providing more employment opportunities.

4.1.2.2. Employment Indicators

For each employment indicator there is data before entering the portfolio and at the end of 2019. As described in the previous Sub-Section, I derive the dependent variables for testing the hypotheses from these indicators. The two different points in time allows to derive the change in these employment indicators per SME, during their active time in the portfolio. In the individual employment datasets, I create the variables *EmploymentChange_F, EmploymentChange_Y18_24* and *EmploymentChange_Y25_35*, respectively. In all three datasets I create *EmploymentChange* accounting for the difference in total employment. By doing this, I can better test whether the investment had a positive or negative effect on the change in these employment indicators. For

[16] For a summary of all the resulting variables, see Appendix A, Table A8, P.72

[17] See Appendix C, Figure C1, P.74, Appendix D, Figure D1, P.86, Appendix E, Figure E1, P.97, for histograms of TimeinPortfolio for Female Employment, Youth Employment 18 – 24 and 25 – 35, respectively.

example, using *NewEmployment_F* as a dependent variable only provides insights into how the different levels of capital invested influences the absolute value of employment reported in 2019. For this research I am more interested in the effect on the relative change from entering the portfolio to exiting the portfolio or at the end of 2019. This can better assess the impact of the investment over the time periods specified.

4.1.2.3. Missing Data from Financial and Employment Indicators

As highlighted several times, the most challenging limitation of this dataset is the fact that there is a large number of missing or unspecified data. This has been recognized by *TJ* as a recurring limitation in impact measurement and analysis. A treatment needs to be devised to account for this missing data. Any treatment will largely affect the format and magnitude of the three datasets but will result in a completer and more representative dataset. One way to account for missing data is to use scores based on averages per sector, region and fund category from the whole dataset. The downside of doing this first is that I would end up with too many imputed datapoints. The data would then not be representative of a real case scenario. That negatively affects both the internal and external validity of this research, since there would be more induced datapoints than real reported datapoints. I recognize the importance of having representative datasets, especially due to the novelty and social relevance of this topic. I, therefore, decide to downsize the datasets using a number of thresholds that should not negatively affect the quality of the data.

First, there is a large number of SMEs that is omitted from each dataset that do not have datapoints on any of the financial and employment indicators, simultaneously. Secondly, SMEs that do not have datapoints on either *TotalCapitalInvested* or *CapitalInvested_DGGF*, and the dependent variable, the respective employment indicator in the dataset, simultaneously, are omitted. For these two investment indicators I also omitted SMEs that had zero values, since they are the main explanatory variables and they simultaneously had no datapoints for any of the employment indicators. The indicators for the SMEs' financial performance, *PriorRevenue, NewRevenue, PriorProfit,* and *NewProfit* receive the same treatment, except that I keep the zero values since these are valuable datapoints for the analysis. After this treatment, the remaining number of missing datapoints for these indicators is profoundly smaller, bringing us closer to a more complete dataset, without omitting valuable data on each of the employment indicators. These are accounted for using the average score between three specifications. More specifically, the average value of SMEs with the same region and sector, region and block, and sector and block, *RegionSector, RegionBlock, SectorBlock,* respectively. It should be noted that these averages are included in the individual datasets but are derived from the initial dataset, not from the datasets obtained after the above treatments. The use of these average scores is aligned with the insights of impact analysts from *TJ*. Through combining these three average scores per missing data point, the value accounts for three unique characteristics of each SME. It should estimate the datapoints more accurately. One limitation is, however, that there is not always an average score for all three factors. I only use the average score if at least two out of three factors have a value, to ensure accurate estimations. Imputing this average score methodology to the missing datapoints leads to only a small remaining number of missing datapoints for these indicators. For simplicity, as this only entailed a handful of SMEs, these are omitted from each of the datasets.

Finally, there are only SMEs that remain with missing datapoints for the employment indicators. Omitting all of them would significantly reduce the datapoints for each dataset, while having valuable datapoints for the other indicators. It is for that reason that I do not start by omitting all of the SMEs with missing datapoints. Using the average score methodology, as described above, I account for these missing datapoints. Only after imputing these datapoints, I omit the remaining missing datapoints for simplicity. After reading all of this, one might believe that the majority of SMEs are omitted, which is true. However, this results in more complete and thus representative datasets for each of the hypotheses. In **Table 7,** I summarize the number of observations per dataset.

Overview of Datapoints per Dataset				
Dataset	*Observations*	*Countries*	*Regions*	*Sectors*
Female Employment	2.394	36	6	17
Youth Employment (18 – 24)	1.736	31	4	16
Youth Employment (25 – 35)	2.325	33	5	16

Table 7: Datasets Characteristics

It should be noted that due to these treatments, all three datasets entail a different distribution for its *Country, Region* and *PrimarySector* variables, as can be seen in **Table 7.** In other words, some country, region and sector specifications from the initial dataset are not represented in the new datasets due to a lack of data in SMEs in those particular groups.

4.1.2.4. Standardising Highly Skewed Data

A number of variables in our dataset are monetary, have large nominal values and are highly skewed. This is dealt with by taking the natural logarithms of these variables. Through standardising the datapoints it allows for a more comprehensive interpretation of the statistical tests. *TotalCapitalInvested* and *CapitalInvested_DGGF* are highly skewed to the left in all three datasets[18]**.** Therefore, I standardize both variables by transforming it into natural logarithms, *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log,* respectively.

The same transformation is relevant for the revenue and profit indicators[19]. However, there exist some datapoints that are equal to zero and for profit also smaller than zero. A logarithmic transformation for those datapoints is undefined. Some SMEs simply may not have existed prior to entry and some may have ceased to exist during their time in the portfolio, both resulting in zero revenues and profit. In addition, SMEs can be making losses in starting up the business or just breaking-even during their time in the portfolio, resulting in zero or below zero profits. All of these scenarios are highly possible in impact investment and need to be accounted for. I deal with this by add a constant to the data in the following format $y = \log{(X + a)}$, where X is the existing value of the revenue and profit indicators.

The constant 'a' for the revenue indicators needs to only be slightly higher than zero and lower than the second lowest datapoint. I choose 'a' to be the mean between zero and the second lowest data point, as illustrated in **Table 8.**

[18] See Appendix C, Figure C1, P.74, Appendix D, Figure D1, P.86, Appendix E, Figure E1, P.97 for histograms of TotalCapitalInvested & CapitalInvested_DGGF for Female Employment, Youth Employment 18 – 24 and 25 – 35, respectively.
[19] Idem ditto for Histograms of Revenue and Profit Indicators

Revenues: Accounting for zero values for logarithmic transformation	
Variable (X)	$(X + a)$.
PriorRevenue	X + 0.615 (a = Mean: 0 – 1.23)
NewRevenue	X + 0.45 (a = Mean: 0 – 0.90)

Table 8: Transformation of zero values in revenue indicators

For the profit indicators it is a bit more complicated, as there are also large negative values, indicating losses. Since it is the objective to add a constant that allows for a logarithm, in other words $X + a$ must be larger than 0, 'a' should be slightly larger than the highest negative datapoint of the respective profit indicators, as illustrated in **Table 9.**

Profits: Accounting for zero and negative values for logarithmic transformation	
Variable (X)	$(X + a)$.
PriorProfit	X + 14.274.429 (a =14.274.427,99 + 1,01)
NewProfit (Female)	X + 35.887.001,01 (a = 35.887.000 + 1,01)
NewProfit (Youth 18 – 24 & 25 – 35	X + 9.792.897 (a = 9.792.895,55 + 1,45)

Table 9: Transformation of zero and negative values in profit indicators

The highest negative number for *NewProfit* in the dataset for female employment is different from that of both youth employment datasets. This is due to the fact that, even though these datasets comprise most of the same data, they are unique.

There are a number of SMEs that have individual comments, such as when an owner is deceased, the SME was liquidated, or operations not yet started. These will be disregarded throughout the statistical methodology. However, they are valuable insights for the subsequent discussion of the results. To test the hypotheses, more data is needed beyond that provided by *DGGF* to derive relevant control variables, which is described in the next Section.

4.2. World Bank Database & International Labour Organisation

As described earlier in this Chapter, I aim to control for relevant country-level characteristics that were highlighted in the literature review. I discussed multiple papers that found that FDI's effect on employment is dependent on country characteristics. These factors range from human capital, to financial sophistication, to quality of institutions and regional policies. These will be accounted for in this research by using control variables for education, population and indices for policy and institutional quality. This data is obtained per country that is specified in each of the *DGGF* datasets for the years 2014 – 2019. They are retrieved from the *WBD* and *ILO*. After accounting for missing datapoints for these variables, I transform the annualized data from these data sources to fit the timeframes that are specific to each SMEs time in the portfolio. Through creating a variable *Timeframe*, based on the time frame to which the data refers; e.g. *2015 – 2018, 2014 – 2019, etc*., I take the average of that timeframe.

4.2.1. Human Capital Quality

The quality of human capital in the countries, in which the *DGGF* invests, is illustrated by indicators for both primary education and secondary education obtained from the WBD, which has retrieved it from the UNESCO Institute for Statistics[20].

Primary education, in general, offers the first and basic levels of reading, writing, math, history, geography, natural science, social science, art and music (UNESCO, 2020). This indicator is illustrated by *SchoolEnrol_T,* which is derived from the variable School Enrolment, Primary (Gross %) in the WDB. It accounts for the percentage of the total population enrolled in primary education, regardless of their age. This means that in some cases this percentage could be higher than 100%, indicating that there are age groups enrolled outside of the official age group that should be enrolled. One interpretation of that is that there are children that repeat grades or enter later than officially supposed to. The reason *gross %* is chosen as opposed to *net %* is that *gross %* gives insights into the capacity and quality of the country's educational system, meaning whether there is sufficient access to primary education and if children follow it according to the official standards. A limitation identified by UNESCO is that it does not take into account the actual attendance of the children but follows the results from annual school surveys. In addition, the variable does not take into account the differences that may exist between countries with respect to the age groups that should officially be in primary education. For the purpose of the hypothesis relating to female employment, I subsequently derived *SchoolEnrol_F,* which specifies the female primary school enrolment. No data for the year 2019 is yet reported on this variable. This is accounted for by taking the average percentage of the preceding 5 years, 2014 – 2018.

The indicator for secondary education is illustrated by *SecEdu_T*, derived from the variable Secondary Education, Pupils (%), which refers to the country's total number of pupils in secondary education, and the variable *Total Population*, as reported by the World Bank. By dividing these two variables, I obtain a percentage of the total population that is in secondary education. For 2019, *Total Population* is not available through the WBD, and is retrieved through the United Nations Department of Economic and Social Affairs (UN, 2020). After obtaining this variable, I identified that there are a number of incomplete missing datapoints that need to be accounted for. I use the average annual percentage changes from the five years before the missing data, as I expect this percentage to grow annually based on the population. Similar to the above variable, *SecEdu_F* is obtained as a control variable for the female employment hypotheses.

In addition, *Population_F* is retrieved to control for the percentage of the total population that identifies as female. *Total population* is transformed into natural logarithm to standardize its distribution. In **Table 10**, I summarize the characteristics of these variables.

[20] UNESCO = United Nations Educational, Scientific and Cultural Organisation

Human Capital Indicators	
Variables	*Description*
SchoolEnrol_T, SchoolEnrol_F,	The percentage of the total, female and male population per country that is enrolled in primary education, relative to the total and female population in the age group that should be enrolled, respectively.
SecEdu_T, SecEdu_F,	The percentage of the total and female population per country that is enrolled in Secondary education, respectively.
Population_Log	Natural Logarithm of the Total Population
Population_F,	The percentage of the total population that identifies as female

Table 10: List of Human Capital Indicators

4.2.2. Country Policy and Institutional Assessment

To account for the quality of government policies and institutions, this research will derive indices from the Country Policy and Institutional Assessment (CPIA) data. It includes four primary definitions consisting of multiple indices, as presented in **Table 11** (World Bank Data Catalogue, 2019).

Country Policy and Institutional Quality Indicators	
<u>Economic Management (EM)</u> • Macroeconomic management, • Fiscal Policy, • Debt Policy	<u>Structural Policies (SP)</u> • Trade, • Financial Sector, • Business Regulatory environment
<u>Policies for Social Inclusion & Equity (PSI)</u> • Gender Equality, • Equity of Public Resource use, • Building Human Resources, • Social Protection and Labour, • Policies and Institutions for Environmental Sustainability	<u>Public Sector Management and Institutions (PSMI)</u> • Property Rights and Rule-Based Governance, • Quality of Budgetary and Financial Management, • Efficiency of Revenue Mobilisation, • Quality of Public Administration, • Transparency, Accountability, and Corruption in the Public Sector

Table 11: List of Country Policy and Institutional Quality Indicators and their Indices

The World Bank assesses each of these measures annually, to score the ability of countries to make effective use of aid. Each index is rated from a scale from 1 – 6, where 1 is very weak and 6 is very strong. The metrics primarily rely on experts that assess the quality of the country's policy and institutional framework. In other words, how well it contributes to the effective use of aid, sustainable growth and poverty reduction (Overseas Development Institutes, 2020).

The use of these indices has a number of shortcomings that this research will need to account for in a scientifically valid manner. The largest shortcoming of these indices is that there are individual countries that are not reported in this assessment. Important for this research is to identify whether these are also countries in our datasets. For example, countries in the African continent largely report on all of these indices. In the Middle East or Central and Southern America individual countries do not regularly report these indices. The only country that does not have any data in our dataset is *Egypt*. For those datapoints I took the regional datapoint from the *Middle East and Northern Africa*, as defined by the World Bank. There are a number of countries that do not have complete data. For these countries I derived a regional average from the existing datapoints of SMEs that are in that region. As with our previous variables, many countries have not yet reported macroeconomic data for the year 2019 that the World Bank publishes. To account for this, I take the average index of the previous five years, 2014 – 2018.

Finally, under the definition of *Structural Policies*; Business Regulatory Environment doesn't have any data; this research omits that index in its analysis. All of the individual indices are used to derive an average index per one of the four main specifications, as described in **Table 11.** These specifications are defined as follows: *EM*, for Economic Management, *SP*, Social Protection *PSI,* for the Policies for Social Inclusion & Equity, and *PSMI,* for the Public Sector Management and Institutions.

4.2.3. Gross Domestic Product

The level of employment in either of our datasets could also be affected by the level of GDP growth in their respective countries. To control for this possible effect *GDP per Capita,* as *GDPpC_Log,* is used. Similar to previous variables, 2019 does not yet have published data and thus this needs to be accounted for. Those datapoints are retrieved by taking the average growth rate of *GDP per Capita Growth* of the previous 5 years and applying that to the datapoints of *GDP per Capita* from 2019. Through this coefficient I aim to raise the discussion about the relationship between GDP and social impact indicators, such as female- and youth employment. However, I do stress that the indicators of female and youth employment are firm-level, not country level data, such as GDP. Therefore, I do not expect a statistically significant coefficient. I want to observe wat kind of role a country's GDP may play in the effect of *DGGF's* investment on the employment indicators in SMEs.

4.3. Descriptive Statistics & Methodology

In this Section, I describe the main statistics of the three separate datasets that are created for each employment indicator and the methodology applied to test the hypotheses. Due to the transformations performed in the previous Section, the distribution of each dataset has been largely affected and are therefore discussed separately. I briefly describe main statistics of each, but I refer to the appendix for complete descriptive statistics tables of the individual datasets.[21] Throughout the following Sub-Sections, I carefully describe my interpretations and the implications this could have on this research and future research.

4.3.1. Female Employment Dataset

4.3.1.1. Descriptive Statistics

In the female employment dataset, there are 2394 SMEs, active in 36 different countries, throughout 6 different world regions. *South-East Asia*, *Europe* and *Sub-Saharan Africa* account for 89.5% of the datapoints, while the remaining 10.5% is divided between *South America*, the *Middle East*, and *South Asia*. *Agri, Food & Fish* and *Wholesale & Retail* account for 1.686 of all SMEs while the remainder is spread throughout 15 other sectors.[22] The most common used investment instrument

[21] See Appendix C, Table C1, P.75 Appendix D, Table D1, P.87, Appendix E, Table E1, P.98 for the Descriptive Statistics Tables of Female- and Youth Employment (18 – 24 and 25 – 35), respectively.
[22] See Appendix C, Table C4, P.77 for the Full List of Sectors

is *Debt*, accounting for 2.261 SMEs, while only 90 SMEs used *Equity.* The remainder is spread across the other instruments. *Financial institutions* have the largest concentration of investments, accounting for 1.728 SMEs, followed by *high impact funds* and *mezzanine finance*. Most SMEs only entered the portfolio in 2019, followed by SMEs that entered in 2017 and in 2018. This accounts for 91.4% of the whole dataset, meaning that from 2014 – 2016, only 8.6% of SMEs entered the portfolio. All the above variables are categorical and will not be included in testing the first hypothesis.

On average, SMEs are active in the portfolio for 15.5 months. This could be due to the fact that most SMEs only entered recently, as described in the above paragraph. There is a slight difference in the means of *TotalCapitalInvested_Log (9.85)* and *CapitalInvestedDGGF_Log (9.54)*. I cannot compare these logarithms economically. However, they do indicate that, on average, SMEs received more capital through the financial intermediary than what was invested by the *DGGF*. In that same logic, I cannot interpret the economic magnitude of the means for both revenue and profit indicators. However, it can be observed that for both the *New* variable is higher than the *Prior* variables. Although this goes beyond the scope of this research, it is an interesting observation as it may also mean that the capital invested has a positive effect on both revenue and profit, which in turn also could affect the ability to employ new people. It is for that reason they are included as control variables for the first hypothesis test. Most importantly, our main dependent variable, *EmploymentChange_F* illustrates that, on average, female employment increases by 9 employees, since entering the portfolio of *DGGF.* The question, of course, remains if this difference in female employment is significantly affected by the invested capital of the financial intermediary and the *DGGF*.

4.3.1.2. Statistical Methodology

For the first hypothesis, I am interested in the relationship between the capital invested and the change in female employment for SMEs in the *DGGF* portfolio.

Hypothesis 1.1. Providing capital to SMEs has a positive impact on female employment change.

This hypothesis relates to the investment objective of *TJ* to improve the level of female employment. In particular, I am interested in the relationship between *EmploymentChange_F* and both *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log.* I run individual regressions for both of these investment indicators, since they are highly correlated (0,9738).[23] To account for the time spent in the portfolio by an SME, *TimeinPortfolio_Log* is included as a control variable. In addition, I also control for the level of female employment before entry as this may also affect the change in female employment. A firm that already has female employment may be more likely to hire more women, depending on its employment objectives. The overall change in employment is also controlled for, as its coefficient could indicate the proportion of female employment that is explained by total employment. In other words, the percentage of total employment change that can be assigned to female employment. Furthermore, all revenue and profit indicators are included as controls as they could be important determinants for employment growth. If revenue grows, a business grows and thus could need new employment opportunities. As explained in Section 4.2., I also want to account for country characteristics, to assess whether they contribute to the quality of

[23] See Appendix C, Table C8, P.79 for Correlogram of Regression Variables

the model, and what their relationship is with female employment change in our dataset. It may be expected that using country-level control variables on firm-level dependent variables results in insignificant explanatory powers. Overall, the results obtained should provide not only an assessment of the impact of the investment but also the quality of the proposed models. First, I will run regressions solely with our main dependent variable and explanatory variable, followed by a model that controls for all firm-level control variables, and finally a model that also includes the country-level control variables. This results in a total of six models, three per investment indicator. The final two model designs are illustrated in **Table 12**.

Final Model Design EmploymentChange_F
Main Explanatory Variable = TotalCapitalInvested_Log
$EmploymentChange_F = TotalCapitalInvested_{Log} + TimeinPortfolio_{Log} + PriorEmployment_F + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_F + SchoolEnrol_F + SchoolEnrol_T + SecEdu_F + SecEdu_T + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$
Main Explanatory Variable = CapitalInvestedDGGF_Log
$EmploymentChange_F = CapitalInvestedDGGF_{Log} + TimeinPortfolio_{Log} + PriorEmployment_F + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_F + SchoolEnrol_F + SchoolEnrol_T + SecEdu_F + SecEdu_T + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$

Table 12: Model Design Including All Control Variables Female Employment

The second and third hypothesis accounts for the fact that our data is spread throughout multiple countries and sectors. As described in the literature review, there are usually differences between such groupings of data on the relationship between investments and its effect on local impact indicators. In the hypotheses, I argue that this difference is also evident in our case study, as SMEs are spread through multiple countries and sectors. First, I test whether a there is at least one pair of countries in the dataset with significantly different means, using a Kruskal-Wallis test.

H2.1: The female employment change in SMEs resulting from the investment is significantly different across the countries of primary operations.

This type of test requires four assumptions to be met. The first one is that the two variables, dependent and independent variable, are either ordinal or continuous. In this case, the dependent variable is the change in female employment, which is a continuous variable. The independent variable is Country or Sector, which is ordinal and consists of 36 independent countries or 16 independent sectors. This satisfies the second assumption that the independent variable needs to be categorical and consisting of two or more independent groups. The third assumption reads that all observations need to be independent. Since each observation pertains to a single SME, this can be assumed in our data. The fourth assumption relates to whether our distributions across countries or sectors are similar. This is important to know, when interpreting the results. I assume that distributions across countries or sectors are not similar since not all have the same number of observations. As described in the descriptive statistics, in this dataset the majority of datapoints is comprised by only a handful of countries and sectors. It is for that reason that the results of this test can only be interpreted as comparing mean ranks, as opposed to median ranks.

To dive into more detail of these differences between pairs in these groups would require individual independent sample t-tests. Conducting such tests for every country pair in the dataset would be inefficient as there are large discrepancies between the number of observations in certain countries. However, I can test it between pairs of regions in which these countries are situated. This is done only for the three regions that have the largest concentration, on the condition that they have sufficient datapoints. The regions that have the most datapoints in each dataset are *Sub-Saharan Africa, South-East Asia* and *Europe,* as presented in the **Table 13.**

Mean Differences Region		
EmploymentChange_F	*Observations*	*Mean*
Europe	733	4,94
Sub-Saharan Africa	509	30,07
South-East Asia	901	1,30
South-Asia	186	4,73
Middle East	62	3,71
South America	3	28,33

Table 13: Mean Differences Largest Regions – Employment_F

It is interesting to observe that *Sub-Saharan Africa* has a much larger mean than *Europe* and *South-East Asia*. One reason could be that female employment is a more prominent objective for those local SMEs. *TJ* has indicated that there are several SMEs, although not quantified, that have specific employment objectives that could make them more likely to hire female employees. This may also be more pronounced in *Sub-Saharan Africa. TJ* can use these results for future investment decisions, knowing in which countries/regions they do well and in which they may want to seek improvements to contribute more to female employment.

The same tests are also conducted for differences between sectors to test the third hypothesis in this dataset.

H3.1: The female employment change in SMEs resulting from the investment is significantly different across the sectors of primary operations.

Since I am also interested in specific differences between sectors, an independent sample t-test is also conducted between the two largest sectors in the dataset, *Agri, Food & Fish,* and *Wholesale & Retail,* based on the fact that they have a similar amount of observations, as presented in **Table 14** [24]. Together, they account for 70% of the SMEs. The other sectors do not have sufficient observations to perform such a test. From **Table 14,** the mean for *Agri, Food & Fish* is larger than *Wholesale & Retail* by 4 more female employees. This could be due to differences in the type of labour needed. *Agri, Food & Fish* may attract more female employment due to the level of education

[24] For the Full Table, see Appendix C, Table C3, P.77

required for *Wholesale & Retail* that is not always achieved by women in developing countries. I test whether this difference is statistically significant.

Mean Differences Sector			
EmploymentChange_F	*Observation*	*Mean*	
Agri, Food & Fish	849		5,76
Wholesale & Retail	837		1,84

Table 14: Mean Differences Largest Regions – Employment_F

Although it is not hypothesized specifically, I want to test for differences in female employment change between two other pairs. Previously, I presented two dummy variables, *ExitedPortfolio* and *FemaleSME.* For both of these, I will conduct an independent sample t-test to evaluate whether there are significant differences between SMEs that are still active on the portfolio or that have already exited it. In addition, whether this can also be identified between SMEs that were previously categorised as female owned and those that were not.

4.3.2. Youth Employment (18 – 24) Dataset

4.3.2.1. Descriptive Statistics

The most evident difference between this youth employment dataset and the other datasets is that it has the least amount of datapoints, namely, 1.736 SMEs. This could be due to the fact that this age group has more unreported labour opportunities, for example informal employment. Unfortunately, impact investors do not have the luxury to obtain that kind of distinction in employment data. Based on the literature review, this could be an interpretation and will be further discussed in the results chapter. These SMEs are distributed over 31 countries, in 4 regions across 16 different sectors. Most of them are located in *South-East Asia*, followed by *Sub-Saharan Africa,* and *South Asia*. Datapoints for *Europe* are profoundly smaller than in the female employment dataset. Intuitively, this is because a female population is larger than a population in this particular age group. The largest portion of SMEs is active in *Agri, Food & Fish,* followed by *Wholesale & Retail, Other Services,* and *Manufacturing.* A large majority of these investments is done through debt, while only small amount through equity or a combination of the two. Similar to the female employment dataset, investments are prominently channelled through *financial institutions*. In addition, the growth of the portfolio is also evident in this dataset due to the increasing number of SMEs that entered the portfolio.

Diving more into the descriptive statistics of the variables that are used in the multivariate regressions, results in similar observations as for female employment. On average, SMEs spend 13.8 months in the portfolio. The mean of *TotalCapitalInvested_Log* (*9,90)* into SMEs is larger than the *CapitalInvestedDGGF_Log (9,58).* Both for revenue and profit the *New* variables also have a higher log-value, on average. This indicates that since the investment, on average, these financial performance measures have increased. Testing this statistically is beyond the scope of this paper but remains an interesting observation for the discussion and future research.

Most importantly, *EmploymentChange_Y18_24* indicates that youth employment in this age group, on average, increased by 3 employees in this portfolio. The question, of course, remains if this change in youth employment in this age group is significantly affected by the invested capital of the financial intermediary and the *DGGF*.

4.3.2.2. Statistical Methodology

For the first hypothesis in this dataset, I am interested in the relationship between *EmploymentChange_Y18_24* and both *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log.*

Hypothesis 1.2. Providing capital to SMEs has a positive impact on youth employment change (18 – 24)

This hypothesis relates to the investment objective of *TJ* to improve the level of youth employment for the age group 18 – 24 years old. The methodology is almost the same as for the female employment hypothesis, except for a number of different control variables. I present six models in total, where only the models including the country-level control variables are slightly different. I do not include the female-specific variables on population and primary- and secondary education. The final model designs with all control variables are presented in **Table 15.** Overall, the results obtained should provide an evaluation of the impact of the investment but also the quality of the proposed models.

Final Model Design EmploymentChange_Y18_24
Main Explanatory Variable = TotalCapitalInvested_Log
$EmploymentChange_{Y18-24} = TotalCapitalInvested_{Log} + TimeinPortfolio_{Log} + PriorEmployment_{Y18-24} + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_{Log} + SchoolEnrol_T + SecEdu_T + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$
Main Explanatory Variable = CapitalInvestedDGGF_Log
$EmploymenChange_{Y18-24} = CapitalInvestedDGGF_{Log} + TimeinPortfolio_{Log} + PriorEmployment_{Y18-24} + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_{Log} + SchoolEnrol_T + SecEdu_T + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$

Table 15: Model Design Including All Control Variables Youth Employment 18 – 24

The second hypothesis is tested by conducting a Kruskal Wallis test, to identify if there is at least one pair in the country group or sector group that has a significantly different mean. First, I test this for differences between countries in the dataset.

H2.2: The youth employment change (18 – 24) in SMEs resulting from the investment is significantly different across the countries of primary operations.

On the regional level, I can, more specifically, determine the statistical significance of the individual directions between regions through an independent sample t-test. I perform this test between *South-East Asia* and *Sub-Saharan African* because they have the largest number datapoints, accounting for 80% of the data. It is interesting to observe that the magnitude of both and the difference between these two regions is a lot smaller in this dataset than in the female employment dataset.

Region Mean Difference		
EmploymentChange_Y18_24	*Observations*	*Mean*
Europe	171	2,93
Sub-Saharan Africa	480	4,85
South-East Asia	901	0,47
South-Asia	184	8,94

Table 16: Mean Differences Largest Regions – Employment_Y18_24

Secondly, a Kruskal Wallis test is performed across sectors.

H3.2: The youth employment change (18 – 24) in SMEs resulting from the investment is significantly different across the sectors of primary operations.

Diving into specific sectors, I perform an independent t-test between the two largest sectors, *Agri, Food, & Fish* and *Wholesale & Retail* that account for 65% of SME's, while the latter on its own accounts for 47%. This large difference in observations may affect the statistical significance of the test. Nonetheless, I perform the test to determine whether the larger mean for *Agri, Food & Fish* is significantly higher than *Wholesale & Retail.*

Mean Differences Sector		
EmploymentChange_Y18_24	*Observation*	*Mean*
Agri, Food & Fish	292	3,17
Wholesale & Retail	821	0,64

Table 17: Mean Differences Largest Sectors – Employment_Y18_24

In this dataset, I also to test for differences in youth employment change within dummy variables *ExitedPortfolio* and *YouthSME.* As previously stated, it would be interesting to observe whether there are statistical differences between SMEs that exited the portfolio and those that are still active. In addition, this is also true for SMEs that were previously defined as a youth SME and those that were not.

4.3.3. Youth Employment (25 – 35) Dataset

4.3.3.1. Descriptive Statistics

The number of datapoints for youth employment (25 – 35) indicate that data on employment in this age group is more accessible for the *DGGF*, in contrast to the age group 18 – 24-year olds. This could be since the younger age group may be more involved in the informal sector and thus more difficult to trace and collect data. A total of 2.325 SMEs is spread throughout 33 countries in 5 different regions. Most SMEs are located in *South-East Asia* and *Europe,* followed by *Sub-Saharan Africa*. *Agri, Food & Fish* and *Wholesale & Retail* remain the largest sectors that are represented in the dataset. SMEs are largely financed through *Debt* and through *Financial Institutions.* Similar to the previous datasets, the growth of the portfolio is evident by the increasing number of SMEs over the years, 2017 – 2019.

On average, SMEs in this dataset are active in the portfolio for 15 months. Once again, this can be explained by the fact that most SMEs have only entered the portfolio in the previous year. The same observation, as in the previous datasets, is made with regards to the difference in *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log*. However, interestingly, *PriorProfit_Log* is higher than *NewProfit_Log*, indicating that in this distribution, profits were higher before entry than as recorded at exit or at the end of 2019. This may be driven by some SMEs that started with zero profits since they did not exist before entry and made losses at the end of 2019. Most importantly, *EmploymentChange_Y25_35* indicates that employment in this age group has, on average, increased by 5 employees, since the investment.

4.3.3.2. Statistical Methodology

The methodology for this dataset is exactly the same as for the previous age group. Except, of course, that the employment variables relating to this age group are used. The first hypothesis in this dataset is described as follows:

Hypothesis 1.3. Providing capital to SMEs has a positive impact on youth employment change (25 – 35)

This hypothesis relates to the investment objective of *TJ* to improve the level of youth employment for the age group 25 – 35 years old. Again, the aim of this paper to assess the proposed models, in addition to the relationship between our main dependent and explanatory variables. I present the models **Table 18:**

Final Model Design EmploymentChange_Y25_35
Main Explanatory Variable = TotalCapitalInvested_Log
$EmploymentChange_{Y25-35} = TotalCapitalInvested_{Log} + TimeinPortfolio_{Log} + PriorEmployment_{Y25-35} + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_{Log} + SchoolEnrol_{T} + SecEdu_{T} + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$
Main Explanatory Variable = CapitalInvestedDGGF_Log
$EmploymenChange_{Y25-35} = CapitalInvestedDGGF_{Log} + TimeinPortfolio_{Log} + PriorEmployment_{Y25-35} + EmploymentChange + PriorRevenue_{Log} + NewRevenue_{Log} + PriorProfit_{Log} + NewProfit_{Log} + Population_{Log} + SchoolEnrol_{T} + SecEdu_{T} + EM_{Index} + SP_{Index} + PSI_{Index} + PSMI_{Index} + GDPpC_{Log}$

Table 18: Model Design Including All Control Variables Youth Employment 25 – 35

For the same reasons expressed in the other datasets, the following hypothesis is tested for differences in employment change across countries this particular age group using the same methodology.

H2.3: The youth employment change (25 – 35) in SMEs resulting from the investment is significantly different across the countries of primary operations.

Table 19 shows that there were many differences in means between the regions where SMEs are primarily active. Similar to the female employment dataset, they are highly concentrated in *Europe, Sub-Saharan Africa* and *South – East Asia*. For these regions I test whether the differences are significant. Although, I do not test for a significant difference between the other regions in the dataset, it is interesting to observe that they seem to be less successful in hiring new employment in this age group. The mean employment change for this age group in the Middle East is negative. This indicates that since the investment, in the limited number of observations, youth employment decreased, on average.

Mean Differences Regions		
EmploymentChange_Y25_35	*Observations*	*Mean*
Europe	730	3,78
Sub-Saharan Africa	490	17,57
South-East Asia	901	0,81
South-Asia	184	2,58
Middle East	20	-7,43

Table 19: Mean Differences Largest Regions – Employment_Y25_35

The same tests are conducted to test the third hypothesis and the extension to test the significance in the difference between the two largest sectors.

H3.3: The youth employment change (25 – 35) in SMEs resulting from the investment is significantly different across the sectors of primary operations.

In this dataset, *Agri, Food, & Fish* and *Wholesale & Retail* account for 72% of SME's, and have a similar number of observations, making it a good pair for testing significant differences in means. It is quite surprising that the largest sector, *Agri, Food & Fish*, has a negative mean for employment change, as can be seen in **Table 20.** This means that a majority of the SMEs, on average, has experienced a decrease in employment in this age group. This change in mean, in contrast to the other age group, for *Agri, Food & Fish* could be due to the fact that SMEs replaced employment from this age group with employment in the younger age group. The increase in the mean for *Wholesale & Retail* relative to the previous age group could also be due to the argument presented earlier. Employment in this sector may require higher education which is achieved in this age group.

Mean Differences Sector		
EmploymentChange_Y25_35	*Observation*	*Mean*
Agri, Food & Fish	845	-0,36
Wholesale & Retail	830	1,00

Table 20: Mean Differences Largest Sectors – Employment_Y25_35

4.3.4. Heteroskedasticity in Standard Errors

In each of the regressions described above I need to account for the fact that there may be heterogeneity in the variance of the residuals. By doing this, I ensure that the results that I obtain are robust. There are multiple ways to test for heteroskedasticity. For all models, I plot the residuals versus the predicted values. In all the datasets, this illustrates a trend towards the zero line, indicating there is heteroskedasticity[25]. A further check is performed through a Breusch-Pagan test, which tests the hypothesis whether the variance of the residuals is homogenous. For all models run, this test results in a p-value of 0.0000, rejecting the null hypothesis that the variance of the residuals is homogenous[26]. It is for that reason that I need to use a specification in all regressions that corrects for this heteroskedasticity.

5. Results & Implications

In this Chapter, I present and analyse the results obtained from all tests conducted. At this stage, I would like to highlight that, in addition to testing the hypothesis, this research assesses whether the models proposed, based on previous literature, are appropriate for impact measurement and analysis. Ultimately, due to the novelty and limitations of research in this field, the results should provide many new insights and suggestions for future research in *SII.*

5.1. The relationship between the investment and female employment

5.1.1. Multivariate Regressions

OLS Regressions – EmploymentChange_F		
EmploymentChange_F	*(1)*	*(2)*
TotalCapitalInvested_Log	3,150**	
	(1,521)	
CapitalInvestedDGGF_Log		4,962**
		(1,996)
Constant	-38,467**	-22,117
	(18,090)	(14,007)
Observations	2.394	2.394
R-squared	0,015	0,012
Robust standard errors in parentheses *** p<0,01, ** p<0,05, * p<0,1		

Table 21: OLS Regression EmploymentChange_F (Excluding Control Variables)

Starting with the first hypothesis, I regress *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log,* individually, with *EmploymentChange_F,* without any control variables, in **Table 21**. In the first model, the coefficient 3,150**, illustrates that a 1% increase in the total level of capital invested, increases the change in female employment by 0,032 "employees". The second model indicates that increasing the capital invested by *DGGF* in the SME, increases the change in female employment by 0,049 "employees". Intuitively, it would make sense to control for the total capital invested in the second model, since the effect of capital invested by the *DGGF* is also determined by the total capital invested. However, since they are largely the same, they are highly correlated and thus may cause multicollinearity and biased results. Secondly, I run the regression including all firm-level control variables for both investment indicators. Subsequently, I include the

[25] See Appendix C, Table C9, P.80, Appendix D, Table D9, P.92, and Appendix E, Table E9, P.103 for these plots, Employment_F, Employment_Y18_24, and Employment_Y25_35., respectively.
[26] See Appendix B, Table C10, P.81, Appendix C, Table D10, P.93 and Appendix D, Table E10, P.104 for these tests, Employment_F, Employment_Y18_24, and Employment_Y25_35., respectively.

country-level control variables. This results in four different models and they are summarized in **Table 22.**

At first sight, a large number of variables have at least statistically significant coefficients in the 90% confidence interval. Second, the R-squares of all four models, are roughly the same and illustrative that the data somewhat varies from the model. This means that adding the country-level control variables does not largely improve the fit of the model. However, it is worth noting that it does not worsen the fit of the model. Adding the country-level control variables slightly decreases the coefficients for the investment indicators in both models and does not affect their significance level. In none of the models, are the female employment level before entry and both profit indicators statistically significant.

In Model (1), in **Table 22,** *TotalCapitalInvested_Log* has a highly significant coefficient, which indicates that a 1% increase in this variable, will increase the change in female employment by 0,026 employees. This effect is slightly larger for *CapitalInvestedDGGF_Log* in Model (2), which increases the change in female employment by 0,039 employees, if increased by 1%. The same interpretations can be made in the other three models. The coefficients for the time spent in the portfolio suggest a negative relationship between the time spent in the portfolio and the change in female employment. More specifically, in Model (1), if *TimeinPortfolio_Log* increases by 1%, then female employment change decreases by 0,052 employees. This result could be driven by the fact that a large majority of SMEs only joined over the past few years and may be more successful in hiring female employees than those that have been in the portfolio longer. Therefore, it could be stated that this relationship does not mean that time itself has a negative impact on female employment change. I would argue that the *DGGF* has become more successful over time to contribute to female employment with new entrants to the portfolio. This, intuitively, makes sense because the investment committee of the fund should also learn to better identify funds that better identify SMEs in which it can deliver more impact. Based on the coefficient of *PriorEmployment_F*, although not statistically significant, SMEs that already have female employment, hire less new female employees. In other words, they may seek a more diverse workforce and also hire male employees. Later in this Section, I test whether there are significant differences between SMEs that were defined as Female-owned and those that were not.

Both revenue indicators in Model (1) and (2), illustrate a negative sign between an SMEs change in female employment and revenue before entry and after exit, or at the end of 2019. More specifically, the higher an SMEs revenue is before entry, the lower the female employment change. The same is true for revenue at exit or at the end of 2019. I cannot derive from these results that an increase in revenue, since the investment, has a negative influence on a company's individual female employment. The relationship between revenue growth and female employment cannot be reliably concluded from the regression. The main reason is that for most of these SMEs, revenue is extremely volatile, especially since most are in early stages of their life cycle. One way to interpret the coefficients is that, overall, larger SMEs with more revenue, are less contributory to female employment than smaller SMEs.

Multivariate Regressions – EmploymentChange_F				
EmploymentChange_F	*(1)*	*(2)*	*(3)*	*(4)*
TotalCapitalInvested_Log	2,624***		2,418***	
	(0,825)		(0,894)	
CapitalInvestedDGGF_Log		3,864***		3,685***
		(1,083)		(1,194)
TimeinPortfolio_Log	-5,151***	-4,915***	-5,481***	-5,359***
	(1,024)	(0,962)	(1,118)	(1,091)
PriorEmployment_F	-0,130	-0,132	-0,118	-0,122
	(0,187)	(0,185)	(0,186)	(0,183)
EmploymentChange	0,534***	0,533***	0,535***	0,534***
	(0,150)	(0,151)	(0,149)	(0,150)
PriorRevenue_Log	-0,460***	-0,403**	-0,414**	-0,351**
	(0,165)	(0,167)	(0,174)	(0,177)
NewRevenue_Log	-2,734***	-2,742***	-2,852***	-2,870***
	(0,288)	(0,279)	(0,301)	(0,296)
PriorProfit_Log	-26,441	-26,691	-25,245	-25,798
	(26,648)	(26,652)	(26,752)	(26,795)
NewProfit_Log	3,285	3,425	3,183	3,340
	(2,338)	(2,330)	(2,252)	(2,246)
Population_F			-75,128	-87,259
			(108,323)	(108,648)
SchoolEnrol_F			432,713**	383,421**
			(172,695)	(175,811)
SchoolEnrol_T			-406,620**	-357,169**
			(159,768)	(163,366)
SecEduc_F			-6,633	-12,674
			(29,910)	(30,838)
SecEdu_T			-79,413	-69,173
			(51,267)	(51,643)
EMIndex			-1,756	-0,881
			(4,435)	(4,507)
SPIndex			-12,981*	-15,188**
			(7,397)	(7,333)
PSIIndex			-17,139*	-18,747*
			(9,686)	(9,610)
PSMIIndex			28,747**	31,677**
			(13,889)	(13,746)
GDPpC_Log			-0,545	-0,416
			(1,402)	(1,417)
Constant	403,128	392,772	433,601	434,560
	(465,176)	(463,141)	(453,665)	(454,412)
Observations	2,394	2,394	2,394	2,394
R-squared	0,775	0,776	0,776	0,777
Robust standard errors in parentheses - *** p<0,01, ** p<0,05, * p<0,1				

Table 22: Multivariate Regressions EmploymentChange_F with Firm- and Country Controls

In other words, investing in smaller SMEs leads to greater positive female employment change, while in larger SMEs this impact is less. The same interpretation can be made about the negative coefficients of *PriorProfit_Log*. *NewProfit_Log* has a small positive non-significant effect on female employment, meaning profit levels after the investment positively affected the change in female employment. It could be argued that profitability of the SMEs also improved. However, as with revenue, due to the volatility of these indicators, I cannot reliably conclude the relationship between these indicators and female employment. One could argue they are, in general, not good independent variables for impact performance analysis in SMEs, at this stage of their life cycle. Nonetheless, I included them in these models since, intuitively, employment change may be dependent on a company's revenue and profit.

Arguably, one of the most interesting coefficients observed is that of the total employment change. *EmploymentChange* is highly significant and positively related to female employment change. Now, logically, if female employment changes, then total employment changes at least in that same magnitude. *EmploymentChange* accounts for both male and female employment change. Therefore, the coefficient in this dataset indicates that if total employment increases by 1 employee, then female employment increases by 0,534*** (0,533***) employees, for Model (1) and Model (2), respectively. In other words, when total employment increases in this portfolio, the majority is female, as 53,4% (53,3%) of this increase is accounted for by female employment.

In Model (3) and (4), the coefficients for both *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log*, only decrease slightly, as described above. In addition, the coefficients for *TimeinPortfolio_Log* and *NewRevenue_Log* indicate a slight increase in their negative effect on *EmploymentChange_F.* The positive effect of *NewProfit_Log* is only marginally decreased. All other firm-level controls have had increases in the magnitude of their coefficients. From the country-level control variables included in Model (3) and (4), only half of them are statistically significant in the 90% confidence interval. This is not surprising, per se, since they are country-level variables, controlling for effects on firm-level variables. The fact that they are not significant in this confidence interval, does not mean that they should not be controlled for. As described in the literature review, variables that pertain to the level of human capital and a country's policies and institutions, also influence the impact of foreign investments. The discussion that follows from this, is to what extent can country-level control variables be included in firm-level data analysis. Since there are variables, such as the level of human capital in a country and the quality of institutions that, for example, protect labour rights, that could influence firm-level employment. In Model (3) and (4), this is evident in the coefficients for *SchoolEnrol_F.* As it increases, this positively effects *EmploymentChange_F.* More specifically, a 1% increase in the female population that follows primary education, increases the change in female employment by 0,04 (4,327** & 3,571**) employees in both models. This effect is negative for *SchoolEnrol_T,* illustrating that male primary education, negatively affects the employment opportunities of women.

The indices for the quality of policies and institutions within a country are almost all negatively related to the female employment change in this dataset, except for *PSMIIndex.* The expectation, based on findings in the literature review, is that a higher quality of policies and institutions positively affect the impact of foreign investments. However, in Model (4), the coefficient of SPI, which also includes an index for Gender Equality, indicates that if this index increases by one unit, this decreases the female employment change by 0.015 employees. The same interpretations can be made for the other indices. Since our dependent variable and other explanatory variables are not all country-level but firm-level, these controls may not be reliable in this format. The discussion remains, whether they are appropriate to include in firm-level models. These controls may bear more statistical meaning if there is more macro-level data available for foreign investments and employment indicators.

Overall, in all four models, the results present a highly significant positive relationship between the investment indicators and female employment change. The coefficients for these investment indicators provide the insight that larger investments also have led to larger increases in female employment change. I retain the first hypothesis in the female employment dataset. Investments by the *DGGF* and the financial intermediary have had an overall positive impact on employment opportunities for the female population in the local economies in which they invest.

5.1.2. Country and Sector Differences

I present a summary of the Kruskal -Wallis test results in **Table 23.**[27] According to the test, there is a high statistically significant difference between female employment change across at least one pair of countries in our dataset. This may be due to differences in employment objectives and gender equality policies in those countries. In other words, some countries are more open to women employment than others. As a result, I do not reject the second hypothesis that there are country significant differences in this dataset.

In **Table 24,** I present a summary of the independent sample t-tests. Between the three largest regions, based on a number of observations, as described in the statistical methodology Section, the results indicate that there are significant differences between the means of each pair[28]. *Sub-Saharan Africa* has a significantly higher mean for *EmploymentChange_F* than both *Europe* and *South-East Asia*. While in turn, *Europe* has a significantly higher mean than *South-East Asia.* This may be due to the fact that in Sub-Saharan Africa, female employment and empowerment is more prominent than in *South-East Asia* or *Europe.* Note here that *Europe* illustrates countries like *Moldova* and *Armenia.*

The Kruskal – Wallis test for sector differences illustrates that there are also high statistically significant differences between at least one pair of sectors for the change in female employment. Therefore, I retain the third hypothesis that there are significant differences between sectors in female employment change. The independent sample t test, as shown in **Table 24,** illustrates that investments into *Agri, Food & Fish* significantly contribute 4 more female employees than in *Wholesale & Retail*. As stated in the statistical methodology Section, this could be due to differences in the type of labour needed in each sector. I argue that some sectors are simply more open to female employment than others. This, of course, is based on stereotypes that some forms of employment are better suited for men than for women. I also argue that in some countries, women do not have the same access to certain education degrees and thus are less likely to be hired into certain positions. It may be that employment in *Agri, Food & Fish* does not require the same kind of labour as *Wholesale & Retail*. In addition, degrees that educate an individual in either directions specific to those sectors may be or not be more attractive to women. However, data on preferences of employment areas or education are not included in this research, thus I cannot reliably underpin these arguments. Nonetheless, they are interesting points of discussion and will be further elaborated in Chapter 6.

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[27] See Appendix C, Tables C11 – C12 P.82 – 83 for the full tables of the Kruskal-Wallis Tests

[28] See Appendix C, Tables C13 – C16, P.83 – 84 for the full tables of these Independent Sample T-Tests

Kruskal-Wallis Test– EmploymentChange_F			
Group	*Chi-Squared*	*Degrees of Freedom*	*Probability*
Countries	1269,244	35	0,0001
Sectors	507,241	16	0,0001

Table 23: Kruskal-Wallis Equality-of-Populations Rank Test for EmploymentChange_F

Independent Sample T Test Summary– EmploymentChange_F			
Mean(A) – Mean (B)	*Ha: diff < 0:* Pr (T < t)	*Ha: diff! =0:* Pr (T > t)	*Ha: diff > 0:* Pr (T > t)
	Regional Differences		
Europe vs. Sub-Saharan Africa	0,0000	0,0000	1,0000
South-East Asia vs. Sub-Saharan Africa	0,0000	0,0000	1,0000
Europe vs. South-East Asia	1,0000	0,0000	0,0000
	Sectors Differences		
Agri, Food & Fish vs. Wholesale & Retail	1,0000	0,0000	0,0000
	Additional Tests		
Active SME vs. Exit SME	0,8411	0,3178	0,1589
Not FemaleSME vs. FemaleSME	0,9574	0,0852	0,0426

Table 24: Independent Sample T-Tests (Unequal Variances) – EmploymentChange_F

In the methodology, I suggested that it could also be interesting to test for mean differences between pairs of groups other than in countries, regions or in sectors. More specifically, differences between SMEs that are still in the portfolio and those that have already exited, or SMEs that were defined as female-owned before entry and those that were not. I present the results of these tests in **Table 24**.[29] On average, active SMEs contributed more to female employment than those that already exited the portfolio. This could mean that the portfolio is, over time, improving its contribution towards female employment through their investments. More specifically, active SMEs have a mean of 9 employees, while exited SMEs have a mean of 7 employees for female employment change. The tests found that this difference between active SMEs and exited SMEs is not significant, mainly due to the fact that there is a large difference in observations. Only 314 SMEs exited, while 2.080 SMEs are still active in the portfolio. In addition, SMEs that were not previously defined as a FemaleSME contributed more to female employment than those that were defined as such, on average. Non-FemaleSMEs almost have double the mean of Female SMEs in female employment change, 11 employees vs. 6 employees. It could be that, as has been argued earlier, that SMEs that are already defined as female, meaning they already have female employment to a certain extent, are less tempted to hire more female employees. This may be true since they aim for a diverse workforce. The test shows that the difference between these two groups is in fact statistically significant at the 5% significance level.

[29] See Appendix C, Table C17 – C18, P.85 for the Full tables of these Independent Sample T-Tests

5.2. The relationship between the investment and youth employment (ages 18 – 24)

5.2.1. Multivariate Regressions

OLS Regressions – EmploymentChange_Y18_24		
EmploymentChange_Y18_24	*(1)*	*(2)*
TotalCapitalInvested_Log	1,030**	
	(0,441)	
CapitalInvestedDGGF_Log		1,727**
		(0,701)
Constant	-7,377*	-13,716**
	(4,065)	(6,411)
Observations	1,736	1,736
R-squared	0,021	0,029
Robust standard errors in parentheses *** p<0,01, ** p<0,05, * p<0,1		

Table 25: OLS Regression EmploymentChange_Y18_24 (Excluding Control Variables)

The results of the model where I separately regress *EmloymentChange_Y18_24* on *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log,* in **Table 25,** indicate a high significant coefficient for both investment indicators. A 1% increase in *TotalCapitalInvested_Log (CapitalInvestedDGGF_Log)*, increases the *EmploymentChange_Y18_24* by 0,01 (0,017) employees. However, these results are highly affected by the inclusion of control variables, both firm-level and country-level ones. In **Table 26,** I present the results for the two models including the firm-level control variables and two models including both firm-level and country-level controls.

Not only did the coefficient for *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log* lose their significance. Their coefficients, simultaneously, changed sign in all four models. For example, in Model (3) when *TotalCapitalInvested_Log* increases by 1%, the *EmploymentChange_Y8_24* decreases by 0,007 employees. Although not statistically significant, this means that the larger investments in the dataset are less contributory to the employment change in this age group. In that thought, smaller investments in the dataset contribute more to the youth employment in this age group. The only firm-level control variable that has a statistically significant coefficient in these models is *PriorEmployment_Y18_24.* This explains that SMEs that already had employees between the ages of 18 – 24 also hired new employees in this age group. Although not significant, the coefficient of *EmploymentChange* illustrates that if it increases by 1 employee, youth employment increases by 0,026 employees. In other words, only 2,6% of all employment increases can be allocated to youth employment in this age group. The coefficient for *Population_Log* illustrates that countries in the dataset with a larger population, were less contributory to youth employment in this age group. In Model (4), if the population increased by 1%, this decreases youth employment by 0.017 employees.

Multivariate Regressions EmploymentChange_Y18_24				
EmploymentChange_Y18_24	*(1)*	*(2)*	*(3)*	*(4)*
TotalCapitalInvested_Log	-0,710		-0,819	
	(0,725)		(0,794)	
CapitalInvestedDGGF_Log		-0,787		-0,847
		(0,955)		(1,029)
TimeinPortfolio_Log	1,402	1,216	1,273	1,129
	(0,945)	(0,850)	(0,935)	(0,874)
PriorEmployment_Y18_24	0,637**	0,633**	0,641**	0,636**
	(0,296)	(0,297)	(0,296)	(0,297)
EmploymentChange	0,026	0,026	0,026	0,026
	(0,027)	(0,027)	(0,027)	(0,027)
PriorRevenue_Log	-0,117	-0,136	-0,079	-0,106
	(0,120)	(0,110)	(0,117)	(0,106)
NewRevenue_Log	0,137	0,100	0,115	0,082
	(0,128)	(0,113)	(0,133)	(0,121)
PriorProfit_Log	12,646	12,645	12,897	12,637
	(9,204)	(9,285)	(9,415)	(9,470)
NewProfit_Log	-7,462	-7,503	-7,743	-7,477
	(8,792)	(8,844)	(8,854)	(8,921)
SchoolEnrol_T			7,711	8,779
			(7,390)	(7,454)
SecEdu_T			55,428	50,474
			(47,870)	(47,633)
Population_Log			-1,687**	-1,762**
			(0,810)	(0,879)
EMIndex			1,433	2,216
			(1,977)	(1,897)
SPIndex			-0,024	-0,433
			(3,809)	(4,072)
PSIIndex			-2,038	-4,175
			(4,936)	(5,060)
PSMIIndex			2,501	4,360
			(7,527)	(7,775)
GDPpC_Log			-1,454*	-1,428*
			(0,844)	(0,842)
Constant	-85,632	-83,475	-60,719	-59,354
	(84,806)	(83,805)	(82,534)	(81,909)
Observations	1,736	1,736	1,736	1,736
R-squared	0,440	0,438	0,445	0,443
Robust standard errors in parentheses *** p<0,01, ** p<0,05, * p<0,1				

Table 26: Multivariate Regressions EmploymentChange_Y18_24 with Firm- and Country Controls

GDPpC_Log indicates that countries in the dataset with a higher GDP per Capita, had a negative youth employment change in this age group. This is an interesting observation, since this would mean that overall, countries with a lower GDP per Capita had a better investment environment for the capital of *DGGF* to contribute to youth employment. However, I must recognize the fact that the independent variables in these models do not explain our dependent variable well, mainly due to its R-squares of around 0,44. In addition, the fact that only three coefficients have significant explanatory power to *EmploymentChange_Y18_24,* proves that the control variables chosen are not enough to determine the significant relationship between the investment and youth employment. It could also mean that it is much more difficult for impact investors to contribute to youth employment. I will further elaborate on this in Chapter 6. As explained, the control variables are chosen based on the insights of previous literature in comparable fields. Using a similar methodology across all three employment indicators was expected to demonstrate similar results. However, these results provide evidence that this is not true for *EmploymentChange_Y18_24*.

One key difference is that in the female employment models, I also included country-level controls for the female population. A limitation of this model could be that I did not include control variables that only pertained to this age group. One reason why I did not do this, is because I did not have the resources to obtain data on the 18 – 24-year old population. Another reason could be that due to the novelty of this data and that it is highly concentrated in the past three years that some SMEs simply do not yet have high quality datapoints that would lead to more statistically significant results. It was observed from the descriptive statistics that the mean *EmploymentChange_Y18_24* was positive. However, I do not find evidence that this change has a positive and significant relationship with either *TotalCapitalInvested_Log* or *CapitalInvestedDGGF_Log*, and thus I reject the first hypothesis for youth employment (18 – 24).

5.2.2. Country and Sector Differences

A summary of the results of the Kruskal Wallis Test, in **Table 27,** indicates that there are significant differences between pairs of countries and sectors in the dataset.[30] The p-value = 0,0001, allows us to reject the null hypothesis that there are no significant differences between pairs of countries and sectors. Therefore, I retain both the hypotheses that there are significant country and sector differences in the change in youth employment (18 – 24).

Diving more into detail for regional differences, the independent sample t test in **Table 28** indicates that *Sub-Saharan Africa* has a significantly larger mean in *EmploymentChange_Y18_24* than *South-East Asia*. In other words, in this dataset, investing in SMEs in *Sub-Saharan Africa* was, on average, more successful in achieving employment in this age group than in *South-East Asia.* This could be due to a number of reasons. For example, some countries may be more active in certain sectors that attract more youth employment. From **Table 28,** I can observe that *Agri Food & Fish* has a significantly larger mean than *Wholesale & Retail* for *EmploymentChange_Y18_24*. I argue that the former is also more pronounced in *Sub-Saharan Africa,* which drives this result. It may also be easier or cheaper for SMEs to hire youth employment in agriculture than in retail. In addition, it could also

[30]See Appendix D, Tables D11 – D12 P.94 – 95 for the full tables of the Kruskal-Wallis Tests

mean that to work in *Wholesale & Retail* you may need a higher education degree that is obtained at an older age.

Kruskal-Wallis Test– EmploymentChange_Y18_24			
Group	*Chi-Squared*	*Degrees of Freedom*	*Probability*
Countries	911,148	30	0,0001
Sectors	250,372	15	0,0001

Table 27: Kruskal-Wallis Equality-of-Populations Rank Test for EmploymentChange_18_24

Similar to the female employment dataset, I also test for significant differences in *EmploymentChange_Y18_24* between SMEs that are active in the portfolio and that have exited. In addition, I test for significant differences between YouthSMEs and SMEs that were not defined as youth owned. I present the results of these tests in **Table 28.**[31] On average, active SMEs contributed approximately the same to youth employment as those that already exited the portfolio. The difference is incredibly small. The results of the test illustrate that this small difference is not significant, which is primarily due to the large difference in observations. The dataset consists of 1.610 active SMEs while only 126 exited the portfolio. On the other hand, SMEs that were defined as youth owned, have a significantly mean than SMEs that were not defined as such. More specifically, on average, the former contributed 1 more employee in this age group than the latter. Although it is not a large difference, it could be interpreted as an indicator that non-youth SMEs are more tempted to hire younger employees than Youth SMEs. It also raises the discussion that YouthSMEs may hire more experienced and older employees to help set up their business. I will follow up on this discussion in Chapter 6.

Independent Sample T Test Summary– EmploymentChange_Y18_24			
Mean(A) – Mean (B)	*Ha: diff < 0:* Pr (T < t)	*Ha: diff! = 0:* Pr (T > t)	*Ha: diff > 0:* Pr (T > t)
	Regional Differences		
South-East Asia vs. Sub-Saharan Africa	0,0000	0,0000	1,0000
	Sector Difference		
Agri, Food & Fish vs. Wholesale & Retail	1,0000	0,0000	0,0000
	Additional Tests		
Active SME vs. Exit SME	0,3230	0,6460	0,6770
Not YouthSME vs. YouthSME	0,9976	0,0047	0,0240

Table 28: Independent Sample T-Tests (Unequal Variances) – EmploymentChange_Y18_24

[31]See Appendix D, Tables D13 – D18, P. 95 – 96 for the full Independent Sample T-Tests

5.3. The relationship between the investment and youth employment (ages 25 – 35).

5.3.1. Multivariate Regressions

OLS Regression– EmploymentChange_Y25_35		
EmploymentChange_Y25_35	*(1)*	*(2)*
TotalCapitalInvested_Log	0,683	
	(1,157)	
CapitalInvestedDGGF_Log		1,540
		(1,224)
Constant	-1,318	-9,272
	(10,055)	(10,427)
Observations	2,325	2,325
R-squared	0,000	0,001
Robust standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1		

Table 29: OLS Regression EmploymentChange_Y25_35 (Excluding Control Variables)

As the results show in **Table 29,** neither *TotalCapitalInvested_Log* and *CapitalInvestedDGGF_Log* have statistically significant coefficients. Nonetheless, the coefficients represent a positive relationship between the investment indicators and *EmploymentChange_Y25_35.* The coefficients can be interpreted in the same way as in the previous datasets. Based on the result derived for the previous age group, I expect similar results for this age group since the regressions entail the same control variables, except for *PriorEmployment_Y25_35.* This means that I expect that the model does not sufficiently explain the fit of the model and thus affects its interpretation. This could be due to omitted variables that should have been included, however, I did not find relevant data. For example, variables that indicate the population in this age group and their specific level of education. The results of the model including firm-level and country-level control variables are presented in **Table 30.**

The explanatory power of our model is too low to conduct a high-quality analysis of the main results. However, I do interpret the important coefficients to determine what may have driven the results and the subsequent low R-squares. The results show a more negative relationship than in the previous age group. In Model (4), the negative coefficient for *TimeinPortfolio_Log* may also be indicative of the growth that the portfolio has experienced and that more recent entries have been more successful in creating employment for this age group. SMEs that have been in the portfolio longer contribute less and thus drive this negative coefficient. Another observation is that the coefficient of total employment change is highly significant and indicates a positive relation with overall employment. Logically, this is because it also captures employment change in this age group. What is interesting is that its coefficient of 0,937 could be interpreted as the portion of total employment change that is described by *EmploymentChange_Y25_35.* In other words, 93,7% of the total employment change in this dataset is driven by employment between ages 25 - 35. In Model (4), the *PSIIndex* is the only country-level variable that has a significant coefficient.

Multivariate Regressions EmploymentChange_Y25_35				
EmploymentChange_Y25_35	*(1)*	*(2)*	*(3)*	*(4)*
TotalCapitalInvested_Log	-1,841		-2,176	
	(1,918)		(2,213)	
CapitalInvestedDGGF_Log		-1,530		-1,917
		(2,405)		(2,875)
TimeinPortfolio_Log	-8,901***	-9,405***	-8,765***	-9,111***
	(1,772)	(1,722)	(2,011)	(1,986)
PriorEmployment_Y25_35	-0,038	-0,062	-0,021	-0,044
	(0,190)	(0,179)	(0,189)	(0,180)
EmploymentChange	0,937**	0,935**	0,939**	0,938**
	(0,407)	(0,408)	(0,406)	(0,407)
PriorRevenue_Log	-0,430	-0,496	-0,451	-0,528
	(0,368)	(0,362)	(0,376)	(0,386)
NewRevenue_Log	-2,668***	-2,820***	-2,736***	-2,865***
	(0,569)	(0,554)	(0,618)	(0,611)
PriorProfit_Log	119,155	119,038	129,278	128,200
	(81,367)	(82,047)	(87,392)	(88,021)
NewProfit_Log	64,662	64,595	54,326	55,361
	(67,791)	(67,779)	(65,668)	(65,870)
Population_Log			-3,011	-3,186
			(2,153)	(2,511)
SchoolEnrol_T			-14,730	-11,695
			(23,450)	(23,585)
SecEdu_T			-122,347	-127,555
			(117,857)	(126,652)
EMIndex			-2,457	-0,442
			(7,866)	(7,508)
SPIndex			-13,300	-13,097
			(12,839)	(12,145)
PSIIndex			-16,755	-20,397*
			(10,739)	(10,896)
PSMIIndex			31,580	33,624
			(21,808)	(20,942)
GDPpC_Log			-3,282	-3,128
			(2,43)	(2,976)
Constant	-2.933,506**	-2.930,271**	-2.820,299**	-2.821,443**
	(1.290,275)	(1.287,395)	(1.220,210)	(1.210,427)
Observations	2,325	2,325	2,325	2,325
R-squared	0,482	0,481	0,485	0,484

Robust standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1

Table 30: Multivariate Regressions EmploymentChange_Y25_35 with Firm- and Country Controls

In the descriptive statistics, it was observed that the mean of *EmploymentChange_Y25_35* was positive. Due to the model fit and the coefficients, I cannot retain the first hypothesis in this dataset and therefore reject the idea that there is a positive significant relationship between the investment indicators and youth employment (25 – 35).

5.3.2. Country and Sector Differences

As expected, the Kruskal-Wallis Test in this dataset also illustrates that there are significant differences between countries and sectors. A summary of the results is presented in **Table 31**[32]**.** P-values of 0,0001 in tests for both groups allow to reject the null hypothesis that there are no significant differences between pairs. Therefore, I retain the hypotheses that there are significant differences between country pairs and sector pairs in the change in youth employment (25 – 35), in this dataset.

For the largest three regions in this dataset, with sufficient observations, I summarize the independent T tests in **Table 32**[33]**.** More specifically, *Sub-Saharan Africa* has a significantly higher mean in *EmploymentChange_Y25_35* than *Europe* and *South – East Asia*. Furthermore, *Europe* has a significantly higher mean than *South – East Asia.* In other words, investments in SMEs that had their primary operations *Sub-Saharan Africa* contributed the most to employment for ages 25 – 35 years old. SMEs in *Sub-Saharan Africa* significantly outperformed those in *Europe* and *South-East Asia,* by 14 and 17 more employees in this age group, on average. It can also be observed that the mean in *EmploymentChange_Y25_35* in *Wholesale & Retail* is significantly larger than in *Agri, Food & Fish.* This is the opposite from the previous age group. I argued that it could be due to the level of required education in certain sectors that resulted in less employment for 18 – 24-year olds in *Wholesale & Retail*, and in turn more employment in that sector for 25 – 35-year olds. This could substantiate my previous argument about difference in educational level requirements for certain sectors.

Kruskal-Wallis Test – EmploymentChange_Y25_35			
Group	*Chi-Squared*	*Degrees of Freedom*	*Probability*
Countries	875,893	32	0,0001
Sectors	129,467	15	0,0001

Table 31: Kruskal-Wallis Equality-of-Populations Rank Test for EmploymentChange_25_35

Testing for a significant difference in the two additional groups, Active SMEs vs. ExitSMEs, and NonYouthSMEs vs. YouthSMEs find that both are significantly different from each other. SMEs that are active in the portfolio significantly outperform SMEs that already exited the portfolio by 5 employees, on average. This, again, illustrates that the *DGGF* is improving its impact on employment through its more recent investments. In addition, SMEs that were defined as a youth SME increase employment significantly less within this age group than those that were not defined as such. Similar to the previous age group, this may be due to their desire to hire more experienced employees to help the younger employees set up the business.

[32] See Appendix E, Tables E11 – E12 P.105 – 106 for the full tables of the Kruskal-Wallis Tests

[33] See Appendix E, Tables E13 – E18 P.106 – 109 for the full tables of the Independent Sample T-Tests

Independent Sample T Test Summary – EmploymentChange_Y25_35			
Mean(A) – Mean (B)	*Ha: diff < 0:* Pr (T < t)	*Ha: diff! = 0:* Pr (T > t)	*Ha: diff > 0:* Pr (T > t)
	Regional Differences		
Europe vs. Sub-Saharan Africa	0,0187	0,0373	0,9813
South-East Asia vs. Sub-Saharan Africa	0,0058	0,0115	0,9942
Europe vs. South-East Asia	1,0000	0,0000	0,0000
	Sector Differences		
Agri, Food & Fish vs. Wholesale & Retail	0,0096	0,0193	0,9904
	Additional Tests		
Active SME vs. Exit SME	0,9955	0,0090	0,0045
Not YouthSME vs. YouthSME	0,9958	0,0085	0,0042

Table 32: Independent Sample T-Tests (Unequal Variances) – EmploymentChange_Y25_35

Having obtained and analysed all results of the hypothesis testing, I will further elaborate and conclude the discussion of the results and their relevance to the *SII* market, the investors of *TJ,* and finally to the research question. This is continued in the next Chapter.

6. Discussion and Conclusion

6.1. Discussion

The results obtained provide several discussion points that need to be further elaborated before I continue with my concluding remarks. In essence, this research is an assessment of the data's usability and of the methodology of previous academic papers in the *SII* market. I made the decision to dive into an impact investment portfolio, because macro-wide impact investment data is not yet publicly available. The approach of this research is to assess the alignment of impact targets, female employment and youth employment, with the UN SDGs, and subsequently explore ways in which this translates into new economic thought, i.e. a wellbeing economy. In the previous Chapter, I presented the results and the interpretation of multivariate regressions and several mean difference tests, for each of the three employment indicators. Based on the models in **Table 22**, I stated that *TJ,* through their investments, positively contributes to the employment of women in SMEs across the countries they invest in. In contrast, neither youth employment models, in **Table 26** and **Table 30,** can retain the hypothesis that the investment has a positive significant effect on the respective youth employment indicators. In other words, it cannot be stated that *TJ* has a measurable statistical positive impact on youth employment in the ages 18 – 24, and 25 – 35. I briefly introduced discussion points that arose from these results, which I will further elaborate on in this Section. An important note, for clarity, is that I am aware that a number of those discussion points will lead to speculation as some are not directly explained through the statistical tests. My aim is to enthuse other academics and students to further develop the landscape of research in the *SII* market with this discussion and as a result create a knowledge base for new economic thinking. In the following Sub-Sections I primarily discuss the most important observations and their implications for future research. They are ideas that both try to explain the results I obtained, or what I did not obtain.

6.1.1. Firm-level vs. Country-level Data

Overall, I raise the argument that if all variables were country-level, I argue that the models would have worked better. However, the inclusion of the country-level variables in my models is valuable and should be done, carefully, taking into account the differences in levels of the data. The controls used are country characteristics that could affect a single firm's ability to contribute to female and youth employment. This is substantiated by the female employment model, in which most of the country characteristics had a significant explanatory power for the respective employment indicators. As described, for youth employment this is not the case. In the youth employment models, I did not include variables for human capital that specifically related to that population, which may have led to our inconclusive results. These were included for female employment and also resulted in a better fit of the model. This type data for youth employment was simply not found but should be considered in future research if it will ever be collected. Furthermore, the inclusion of country-level control variables only mildly contributed to the data fit in the models. This could indicate that other control variables should, additionally, be considered. The question that follows is what kind of variables should then be included in the models. Additional controls could be data on labour union presence, formal and informal employment and quality of work indices. Unfortunately, sufficient data on these indicators is not publicly available for the relevant countries, or not available at all.

6.1.2. The Role of the Financial Intermediary

As was exemplified in Chapter 2, GIIN (2019) indicates that there are differences in target impact objectives between impact investors. The decision in which impact objective they want to invest, also affects the decision in what type of financial intermediary they invest. In *DGGF's* portfolio, the majority of investments is channelled through financial institutions, which are typically micro financiers, MFIs. SMEs that apply for microloans, through financial intermediaries, might not be looking to employ more people but use the capital injection to cover their working capital. The financial intermediaries should collect and report data that describes the intentions of the investee. If it is known what the capital invested will be used for, this might also help identify better what kind of impact is expected and what has occurred. In other words, not only are the target impact objectives from the investor important, but also the objectives of the investee. For example, if the objective of the investee is to use the capital injection to further grow the business, i.e. increase their labour force, and after a couple of years the data illustrates they did not do so, this should effect the impact analysis differently than if they did not intend to increase employment in the first place.

TJ stated that some of the financial intermediaries distribute surveys among the SMEs to collect data on firm-level variables. This should become more common practice among all impact investors, to gather more valuable data from the firms they invest in. More data would also be valuable when considering the counterfactual, as highlighted in Chapter 3. For impact investors, their contribution is relative, not only to before the investment, but also to a hypothetical case where their investment would not have taken place. A well-developed methodology to account for this concept in the dataset was not found, therefore I cannot quantify the counterfactual. One method to obtain insights into this concept is to identify the objective of the SME. I previously argued that this could be important for impact analysis. If it is possible to collect data on the reasons why SMEs apply for capital, then it may be possible to determine better what could have occurred without the capital invested. It makes sense that to apply for a loan, the SME must provide certain information that described the need of the capital invested. This information should then be turned into comprehensive data, e.g. financial forecasts of SME without capital investment.

In addition, more data on the SMEs before entry may also be indicative of the SMEs' context. In the dataset, *TJ* did report on a dummy variable for whether an SME was fragile before entering the portfolio. I did not include this variable because I did not find it relevant for the scope of my hypotheses. However, if this research would have been aimed at evaluating every single aspect of the dataset it may have resulted in a better conclusion about the counterfactual. If the SME was fragile, then one could have assumed that without the capital invested the SME would have likely not survived. When considering this counterfactual, this kind of interpretation can then better assess the impact of the investment. Although, one can never know for certain what the counterfactual is, because, evidently, it never happened. I argue that the role of financial intermediaries is important for impact investors and analysts, and ultimately researchers, to collect this type data more frequently. Impact investors can subsequently exert sufficient effort to incentivise the financial intermediaries to collect this type of data before delegating their capital.

6.1.3. Divergent Results for Employment Indicators

There is a large difference in the models between the three different employment indicators. As described, female employment had a somewhat good fit, however, both youth employment models did not. A first argument for this result is that it may be more difficult for impact investors to target youth employment because it entails a smaller proportion of the total population. Intuitively, there are more people that identify as female than those that have the age of 18 – 24 or 25 – 35. In addition, SMEs may not benefit from youth employment since they need more experienced, generally older, employees to help establish their business. From the descriptive statistics tables, it can also be observed that female employment change is, on average, 9, while in youth employment this is 3 and 5 for 18 – 24, and 25 – 35, respectively[34]. This could also be due to investment strategy of *TJ,* that they simply invest in countries and sectors where they have learned that they can contribute more to female employment. More specifically, it could be true that they invest in funds that have a primary objective to contribute to female employment as opposed to youth employment. During talks with *TJ,* I did not find evidence that their incentive to contribute to female employment is higher than for youth employment. These employment objectives are, ideally, equally important in their investment decisions. The results may be interpreted by *TJ* as that they should target youth employment more when deciding in which funds to invest.

Another perspective that may have led to these results is the fact that the SMEs are active in different sectors. *DGGF* invests heavily in the *Agri, Food & Fish* and the *Wholesale & Retail* sectors, which could be evidence that those sectors are more attractive to achieve their employment objectives. The Kruskal Wallis Tests, in all three employment groups, illustrate that in the *DGGF's* portfolio, there are significant differences between pairs of sectors, in addition to pairs of countries. In more

[34] See Appendix C, Table C1, P.75 Appendix D, Table D1, P.87, Appendix E, Table E1, P.98 for the Descriptive Statistics Tables of Female- and Youth Employment (18 – 24 and 25 – 35), respectively.

depth, I found that between these two largest sectors there is also a significant difference between them. Similarly, this could also be due to employment preferences of females or between ages. This may also be related to the type or level of education needed for employment in that sector. Since these demographics may have different preferences or other levels of educational attainment, this could also lead to different results. One way to substantiate this argument would be to research more in detail the education levels and preferences of the population in a country, or in a sector in these demographics. One can imagine that someone that is aged between 18 – 24, does not have the same educational level as someone from 25 – 35. In addition, working in agriculture or fishing may not require the same type of education as someone working in wholesale and retail. In turn, this may result in a different workforce due to preferences among those demographics. Going into more depth to explain why these differences exist across countries and sectors would require more data on country-level indicators for education levels and preferences across female and youth demographics.

I have, briefly, described the relationship with total employment for the individual employment objectives. Although, I did not test the relationship between the investment and total employment, I stated that the coefficient of each model does illustrate the proportion of employment change, relative to total employment change. For all three employment indicators this relationship is positive, and for *EmploymentChange_F* and *EmploymentChange_Y25_35*, highly significant. Logically it makes sense that this is positive, since total employment entails all three employment indicators. From that I can derive that *TJ* also has a positive impact on total employment, even though I do not determine whether this is effect is statistically significant. This is an opportunity for future researchers to not only focus on testing in specific demographics, but also keeping in mind the value of total employment change.

6.1.4. Linking the Results to the UN SDGs

The analysis of the results indicates that foreign investments in the *SII* market can play a valuable role in creating employment opportunities through financing SMEs. Ultimately, *TJ* contributes to the achievement of SDG target 8.3, and subsequently SDG 8. By doing so, they not only create jobs but also ensure an income for the local population, allowing them to consume more, which leads to more local economic prosperity. These second order effects can spill over to the achievement of other SDGs, and also brings back the insight from the FMO (2019), that there should be a distinction between output measures and outcome measures. In this research, this distinction can be made, where output is represented by the employment indicators, and I argue the outcomes are, as named above, increased income, more consumption and thus more economic prosperity. The relationships with these outcomes are not proven by this research, yet simply offer more dimensions that should be considered. This provides opportunities for future research to explore the relationships between output measures and outcome measures more in depth. These outcomes spill over the primary effect to other SDGs, such as SDG 1, no poverty, since employment also creates incomes for households, which in turn can also positively affect a household's health and wellbeing, relating to SDG 3. Furthermore, since I investigated and found a positive effect on female employment, I can conclude that *TJ* also contributes to SDG 5, gender equality. In addition, more income can lead to more consumption of food, nourishing local communities, which contributes to SDG 2, no hunger. It may also be true that, although I could not conclude they did, contributing to youth employment could lead to more investment into education as job prospects for younger people would be positively affected. These are all interesting relationships in which future research can further explore the integration of UN SDGs in foreign investment decision making and economic thought as a whole.

Although I came across many limitations in this research, primarily due to the challenge of collecting data in the *SII* market, this discussion of the results and all the insights given from *FMO, TJ, Oiko, WEAll* and other impact investment professionals can come to a final conclusion on the main research question.

6.2. Conclusion

The research question that this paper explores is *"Are the United Nations Sustainable Development Goals a comprehensive guideline to conceptualise a Wellbeing Economy?"*. I argued that a wellbeing economy should be an economic system where factors such as human and ecological wellbeing are central to decision-making. One such system, *the Doughnut Economy*, is primarily based on the agenda of the UN SDG's. As a result, the framework of the UN SDG's could play a key role in conceptualising a wellbeing economy. In the introduction, I stated that the OECD argues that, in general, foreign investment will and should play a large role in the achievement of the UN SDGs. It is for that reason that I approached this research question by analysing foreign direct investments, in the recently developed *SII* market. This market entails foreign investments that target social impact categories instead of only maximising their own financial return. Based on data collected by the GIIN, this research dives into SDG 8.3, that describes the need to support financial inclusion of, otherwise financially constraint, SMEs to support local employment objectives, which can lead to increased economic prosperity. I investigated whether the *DGGF*'s investment, in SMEs across multiple developing regions and countries, had a positive significant relationship with local employment objectives, female employment, and youth employment (18 – 24) and (25 – 35). Employment was defined by *TJ* as a paid job, working 8 or more hours per day, excluding temporary employees. This offers certainty that the data collected on these employment measures is representative of a decent job in the formal sector. This thesis is, additionally, an assessment of traditional FDI academic research models for the *SII* market. I conclude that the models, with human capital indicators and sophistication of country policies and institution indices, should be further developed in statistical analysis of the *SII* market. It cannot be repeated enough that it is crucial for future research to further explore methodologies in academic research that are appropriate for the *SII* market.

Overall, the findings illustrate that *TJ*, through the *DGGF*, is improving their impact on employment since the fund was established. Over time they have learned to better contribute to female and youth employment and to further grow its portfolio by increasing the number of investments, reaching out to more SMEs. Our models indicate that their investments positively and significantly contribute to female employment. I cannot conclude the same for both youth employment indicators. These results support the efforts to further mature and sophisticate the *SII* market, to ensure that their role in achieving the UN SDGs is put to valuable use. Through the investments, *TJ* has proven to contribute to the achievement of SDG target 8.3, and subsequently SDG 8. I argued that this contribution can largely spill over to the achievement of other SDGs, such as SDG 1, 2, 3 and 5. This should be further investigated in future research. Furthermore, it is crucial for the *SII* market to develop a knowledge base on impact measurement methodology and impact (e)valuation for both academic and policy- and practice-oriented research. In addition, it remains invaluable to assess the achievement of the UN SDGs. Only by having frequent evaluations and analyses of how we, as a population, are being successful in the achievement of these goals can we learn to develop economic models that consider the global issues of these times, which the UN SDGs already identifies so thoroughly. The *Doughnut Economy* model designed by Raworth (2018) is already a step into the right direction and this research contributes to the knowledge base of an economic model based on the UN SDGs.

Finally, I conclude that putting the UN SDGs at the forefront of investment decisions and impact measurement analysis can provide a comprehensive framework, to link financial return with social impact indicators in foreign investment. Subsequently, this should transform traditional economic thought across financial markets to include more socially relevant indicators that entail human and ecological wellbeing. In that light, I hope that this research, although with its many limitations, enthuses other academics and professionals to further explore this research question with other SDGs and to contribute to the knowledge base of a *Wellbeing Economy.*

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8. Appendices

8.1. APPENDIX A: Figures & Tables

The United Nations Sustainable Development Goals

Goal	*Description*
1 – No Poverty	End poverty in all its forms everywhere
2 – Zero Hunger	End hunger, achieve food security and improved nutrition and promote sustainable agriculture
3 – Good Health and Wellbeing	Ensure healthy lives and promote wellbeing for all at all ages
4 – Quality Education	Ensure inclusive and quality education for all and promote lifelong learning
5 – Gender Equality	Achieve gender equality and empower all women and girls
6 – Clean Water and Sanitation	Ensure access to water and sanitation for all
7 – Affordable and Clean Energy	Ensure access to affordable, reliable, sustainable and modern energy for all
8 – Decent Work and Economic Growth	Promote inclusive and sustainable economic growth, employment and decent work for all
9 – Industry, Innovation, and Infrastructure	Build resilient infrastructure promote sustainable industrialization and foster innovation
10 – Reduced Inequalities	Reduce inequality within and among countries
11 – Sustainable Cities and Communities	Make cities inclusive, safe, resilient and sustainable
12 – Responsible Consumption and Production	Ensure sustainable consumption and production patterns
13 – Climate Action	Take urgent action to combat climate change and its impacts
14 – Life Below Water	Conserve and sustainably use the oceans, seas and marine resources
15 – Life on Land	Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss
16 – Peace, Justice and Strong Institutions	Promote just, peaceful and inclusive societies
17 – Partnerships for the Goals	Revitalize the global partnership for sustainable development

Table A1: The UN SDG's overview

Diagram of a Doughnut Economy

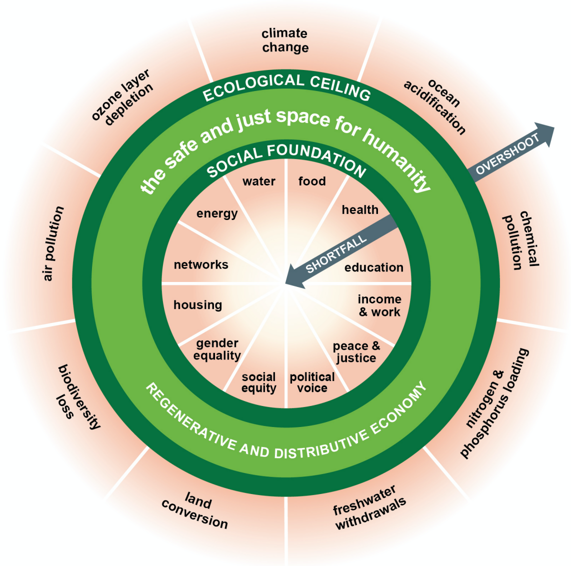


Figure A1 – Doughnut Economics (Raworth, 2018)

Target Impact Categories

Category	*Percentage of Respondents*
Employment	71%
Agriculture	63%

Financial Services	62%
Diversity & Inclusion, including gender and racial equity	60%
Health	60%
Education	56%
Energy	56%
Climate	54%
Real Estate, including Housing	43%
Water	42%
Waste	40%
Pollution	36%
Biodiversity & Ecosystems	32%
Land	30%
Air	28%
Oceans and Coastal Zones	19%
Other	8%

Table A2: All Target Impact Categories, identified by GIIN.
Source: GIIN, The State of Impact Measurement and Management Practice, Second Edition.

Research Topics in Social Impact Investment		
Community Finance	Cooperative and Mutual Finance	Environmental, Social and Governance (ESG)
Alternative Finance	Ethical Banking	Responsible Investment
Crowdfunding	Microfinance	Green Investment
Development Finance	Social Impact Measurement	
The Social and Solidarity Economy	Social Innovation	

Table A3: Focus topics in academic research related to social impact investment
Source: Daggers & Nicholls (2016)

Investability of the Sustainable Development Goals	
Goal	*Description*
1	Investable & Potential for Acknowledged Transformational Leader (ATL)
2	Investable & Potential for Acknowledged Transformational Leader (ATL)

3	Investable & Potential for Acknowledged Transformational Leader (ATL)
4	Investable & Potential for Acknowledged Transformational Leader (ATL)
5	Investable & Potential for Acknowledged Transformational Leader (ATL)
6	Investable & Potential for Acknowledged Transformational Leader (ATL)
7	Investable & Potential for Acknowledged Transformational Leader (ATL)
8	Potential for Acknowledged Transformational Leader (ATL)
9	Investable & Potential for Acknowledged Transformational Leader (ATL)
10	Potential for Acknowledged Transformational Leader (ATL)
11	Investable & Potential for Acknowledged Transformational Leader (ATL)
12	Investable & Potential for Acknowledged Transformational Leader (ATL)
13	Investable & Potential for Acknowledged Transformational Leader (ATL)
14	Investable & Potential for Acknowledged Transformational Leader (ATL)
15	Investable & Potential for Acknowledged Transformational Leader (ATL)
16	Not Investable
17	Not investable

Table A4: Measurability of UN SDG's according to APG & PGGM

The Dutch SDGI Initiative		
Signatories		
ABN-AMRO	Achmea Investment Management	Actiam (The Responsible Investor)
AEGON	APG	ASN Bank
ASR (de Nederlandse verzekeringsmaatschappij voor alle verzekeringen)	Delta Lloyd	FMO
ING	MN	NIBC
Nationale Nederlanden	PGGM	Robeco
Rabobank	Triodos Investment Management	
Enabling Networks		
Phenix Capital (Impact Summit Europe)	PYMWYMIC	VBDO
Facilitators		
SDG Charter	C-Change	

Table A5: List of Signatories Dutch SDGI (Source: (SDGI, 2016)**)**

Working Group Members of SDG Impact Indicators Report		
ABN-AMRO	Achmea Investment Management	Actiam (The Responsible Investor)

APG	ASR (de Nederlandse verzekeringsmaatschappij voor alle verzekeringen)	FMO
ING	Kempen	Van Lanschot
MN	Nationale Nederlanden	Philips
PGGM	Rabobank	Robeco
TKP Investments	Triodos Investment Management	Unilever & Univest Company

Table A6: List of Organisations (Source: (De Nederlandsche Bank, 2017)**)**

List of Sector Definitions	
Agri, Food & Fish	A – Agriculture, forestry and fishing
Manufacturing	C – Manufacturing
Financial Services	K – Financial and insurance activities
Wholesale & Retail	G – Wholesale and retail trade; repair of motor vehicles and motorcycles
Transportation & Storage	H – Transportation and storage
Water Supply	E – Water supply; sewerage, waste management and remediation activities
Education	P – Education
Accommodation & Food	I – Accommodation and food service activities
Real Estate	L – Real estate activities
Construction	F – Construction
Information & Communication	J – Information and communication
Health & Social Work	Q – Human health and social work activities
Other Services	S – Other service activities
Electricity, Gas, Steam & AC Supply	D – Electricity, gas, steam and air conditioning supply
Administrative & Support	N – Administrative and support service activities
Science & Technique	M – Professional, scientific and technical activities
Mining & Quarrying	B – Mining and quarrying
Entertainment & Recreation	R – Arts, entertainment and recreation
Activities of Households as Employers	T – Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
Unknown	n/a

Table A7: List of Sectors of Primary Economic Activity and Initial Specification

Summary of DGGF Dataset Variables	
Fund	Categorical – All Financial Intermediaries (Funds) are numbered by *TJ* in the dataset.

FundCategory	Categorical – The type of fund that best defines their investment portfolio
SMEName	Categorical – All SMEs in the dataset are defined by a number ("SME xxxx")
Country	Categorical – Country in which SME has its primary operations
Region	Categorical – Region in which *Country* of primary operations is situated
PrimarySector	Categorical – Sector in which SME has its primary operations
InvestmentInstrument	Categorical – Investment Instrument used by FI to finance SME
ExitedPortfolio	Dummy – indicated whether a SME has exited the portfolio, through paying off loan or repurchasing equity.
TimeFrame	Categorical – Indicative of the year of entry and, if applicable, year of exit. In case there is no exit, 2019 is used as the final year of data recording.
TimeinPortfolio	Numerical – Indicates the total number of months the SME has been in the portfolio
TimeinPortfolio_Log	Natural logarithm of TimeinPortfolio
TotalCapitalInvested_Log	Logarithmic Transformation of the Total Capital Invested in the SME by the financial intermediary
CapitalInvestedDGGF_Log	Logarithmic Transformation of the Capital Invested by DGGF that was allocated to that SME via the respective financial intermediary.
PriorRevenue_Log	Logarithmic Transformation of the Revenue reported before entering the portfolio
NewRevenue_Log	Logarithmic Transformation of the Revenue reported at end of 2019, or if applicable, when exited the portfolio
PriorProfit_Log	Logarithmic Transformation of the Profit reported before entering the portfolio
NewProfit_Log	Logarithmic Transformation of the Profit reported at end of 2019, or if applicable, when exited the portfolio
Female SME	Dummy – Indicative of whether the SME met the IFC's characterisation of a female-owned SME
Youth SME	Dummy – Indicative of whether the SME met the IFC's characterisation of a youth-owned SME
PriorEmployment	Total employment of SME prior to entry of the portfolio
NewEmployment	Total employment of SME at the end of 2019
EmploymentChange	The difference between the above two employment variables
PriorEmployment_F	Total female employment of SME prior to entry of the portfolio
NewEmployment_F	Total female employment of SME at the end of 2019
EmploymentChange_F	The difference between the above two female employment variables
PriorEmployment_Y18_24	Total youth employment, ages 18 – 24, of SME prior to entry of the portfolio
NewEmployment_Y18_24	Total youth employment, ages 18 – 24, of SME at the end of 2019
EmploymentChange_Y18_24	The difference between the above two youth employment variables
PriorEmployment_Y25_35	Total youth employment, ages 25 – 35, of SME prior to entry of the portfolio
NewEmployment_Y25_35	Total youth employment, ages 25 – 35, of SME at the end of 2019
EmploymentChange_Y25_35	The difference between the above two youth employment variables

Table A8: Summary of DGGF Variables

8.2. APPENDIX B: United Nations Sustainable Development Goal 8 - Targets

8.1 Sustain per capita economic growth in accordance with national circumstances and, in particular, at least 7 per cent gross domestic product growth per annum in the least developed countries

8.2 Achieve higher levels of economic productivity through diversification, technological upgrading and innovation, including through a focus on high value added and labour-intensive sectors

8.3 Promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial services

8.4 Improve progressively, through 2030, global resource efficiency in consumption and production and endeavour to decouple economic growth from environmental degradation, in accordance with the 10-year framework of programmes on sustainable consumption and production, with developed countries taking the lead

8.5 By 2030, achieve full and productive employment and decent work for all women and men, including for young people and persons with disabilities, and equal pay for work of equal value

8.6 By 2020, substantially reduce the proportion of youth not in employment, education or training

8.7 Take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labour, including recruitment and use of child soldiers, and by 2025 end child labour in all its forms

8.8 Protect labour rights and promote safe and secure working environments for all workers, including migrant workers, in particular women migrants, and those in precarious employment

8.9 By 2030, devise and implement policies to promote sustainable tourism that creates jobs and promotes local culture and products

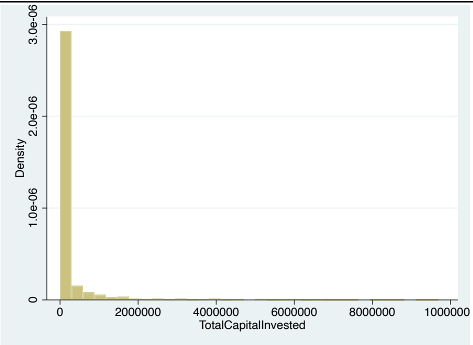
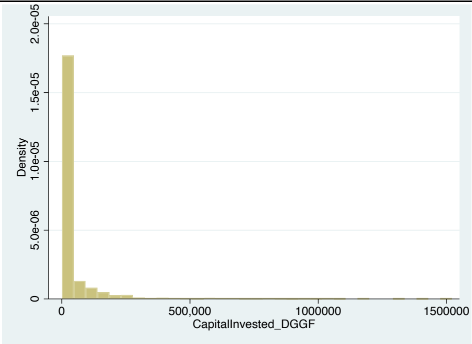
8.10 Strengthen the capacity of domestic financial institutions to encourage and expand access to banking, insurance and financial services for all

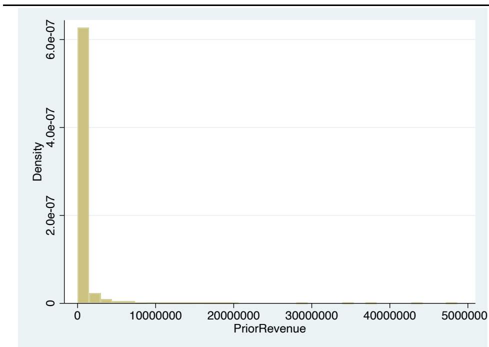
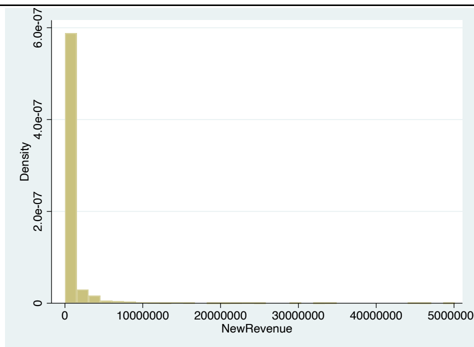
8.A Increase Aid for Trade support for developing countries, in particular least developed countries, including through the Enhanced Integrated Framework for Trade-Related Technical Assistance to Least Developed Countries

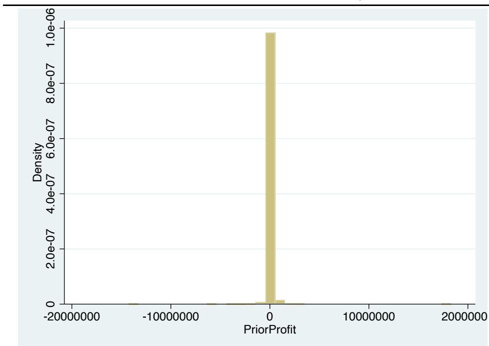
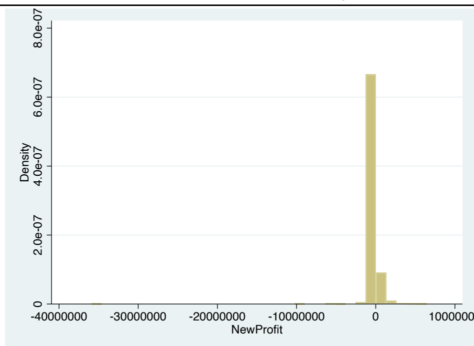
8.B By 2020, develop and operationalize a global strategy for youth employment and implement the Global Jobs Pact of the International Labour Organization

8.3. APPENDIX C: Female Employment Figures & Data Tables

Histograms Female Employment Dataset

TotalCapitalInvested	*Capital Invested DGGF*
	

PriorRevenue	*NewRevenue*
	

PriorProfit	*NewProfit*
	

TimeinPortfolio

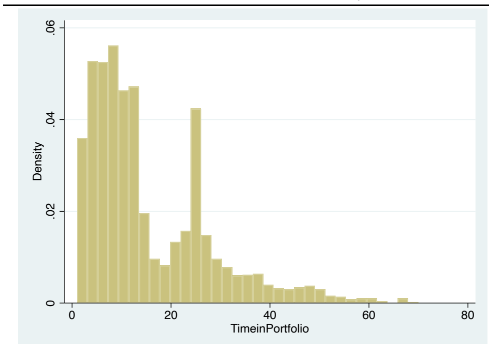


Figure C1: Histograms Female Employment Dataset

Descriptive Statistics Female Employment Dataset

Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*

TotalCapitalInvested_Log	2.394	9,85	1,89	7,38	16,09
CapitalInvestedDGGF_Log	2.394	9,54	1,35	6,51	14,24
TimeinPorftolio	2.394	15,51	12,23	1	70
TimeinPortfolio_Log	2.394	2,422	0,85	0	4.25
FemaleSME	2.394	0,35	0,48	0	1,00
ExitedPortfolio	2.394	0,13	0,34	0	1
PriorEmployment	2.394	17,10	74,82	0	2.342
NewEmployment	2.394	24,30	150,72	0	5.588
EmploymentChange	2.394	7,20	83,60	-228	3.246
PriorEmployment_F	2.394	7,07	36,33	0	1.449
NewEmployment_F	2.394	15,97	83,01	0	3.422
EmploymentChange_F	2.394	8,90	55,08	-364	1.973
Training	2.394	0,41	0,49	0	1
EMIndex	2.394	3,51	0,31	2,42	4
SPIndex	2.394	2,90	0,34	2,25	3,29
PSIIndex	2.394	3,51	0,24	2,64	3,90
PSMIIndex	2.394	3,07	0,24	2,25	3,32
GDPpCGrowth	2.394	0,03	0,02	-0,00	0,07
Population_F	2.394	0,51	0,01	0,45	0,53
SchoolEnrol_F	2.394	1,02	0,05	0,80	1,10
SchoolEnrol_T	2.394	1,04	0,05	0,81	1,12
SecEduc_F	2.394	0,49	0,02	0,40	0,53
SecEdu_T	2.394	0,07	0,01	0,03	0,14
PriorRevenue_Log	2.394	9,15	4,00	-0,49	17,70
NewRevenue_Log	2.394	10,24	3,48	-0,80	17,73
PriorProfit_Log	2.394	16,47	0,34	0,01	17,30
NewProfit_Log	2.394	17,39	0,36	0,01	17,56
GDPpC_Log	2.394	8,46	0,93	6,35	10,00

Table C1: Descriptive Statistics Dataset Female Employment

Country Distribution			
Country	*Observations*	*Percentage*	*Cumulative*
Afghanistan	3	0,13	0,13
Armenia	514	21,47	21,6
Bangladesh	3	0,13	21,72
Cambodia	9	0,38	22,1
Cameroon	1	0,04	22,14
Colombia	1	0,04	22,18
Côte D'Ivoire	11	0,46	22,64
Côte d'Ivoire	1	0,04	22,68
Democratic Republic of the Congo	18	0,75	23,43
Egypt	22	0,92	24,35
Ethiopia	4	0,17	24,52
Georgia	17	0,71	25,23
Ghana	27	1,13	26,36
India	20	0,84	27,19
Indonesia	8	0,33	27,53
Jordan	39	1,63	29,16
Kenya	51	2,13	31,29
Lao People's Democratic Republic	3	0,13	31,41
Madagascar	1	0,04	31,45
Mauritius	2	0,08	31,54
Moldova	202	8,44	39,97
Myanmar	874	36,51	76,48
Nepal	8	0,33	76,82
Nigeria	35	1,46	78,28
Peru	2	0,08	78,36
Philippines	5	0,21	78,57
Rwanda	22	0,92	79,49
Senegal	4	0,17	79,66
South Africa	26	1,09	80,74
South Sudan	7	0,29	81,04
Sri Lanka	152	6,35	87,39
Tanzania	247	10,32	97,7
Uganda	37	1,55	99,25
United Arab Emirates	1	0,04	99,29
Vietnam	2	0,08	99,37
Zambia	15	0,63	100

Table C2: Country Distribution Female Employment

Region Distribution			
Region	*Observations*	*Percentage*	*Cumulative*
Europe	733	30,62	30,62
Middle East	62	2,59	33,21
South America	3	0,13	33,33
South Asia	186	7,77	41,1
South-East Asia	901	37,64	78,74
Sub-Saharan Africa	509	21,26	100

Table C3: Region Distribution Female Employment

Sector Distribution			
PrimarySector	*Observations*	*Percentage*	*Cumulative*
Accommodation & Food	44	1,84	1,84
Administrative & Support	3	0,13	1,96
Agri, Food & Fish	849	35,46	37,43
Construction	15	0,63	38,05
Education	35	1,46	39,52
Electricity, Gas, Steam & AC Supply	12	0,5	40,02
Financial Services	11	0,46	40,48
Health & Social Work	52	2,17	42,65
Information & Communication	17	0,71	43,36
Manufacturing	187	7,81	51,17
Mining & Quarrying	4	0,17	51,34
Other Services	289	12,07	63,41
Real Estate	4	0,17	63,58
Science & Technique	11	0,46	64,04
Transportation & Storage	17	0,71	64,75
Water Supply	7	0,29	65,04
Wholesale & Retail	837	34,96	100

Table C4: Sector Distribution Female Employment

TimeFrame Distribution			
TimeFrame	*Observations*	*Percentage*	*Cumulative*
2014-2018	1	0,04	0,04
2014-2019	14	0,58	0,63
2015-2018	5	0,21	0,84
2015-2019	53	2,21	3,05
2016	2	0,08	3,13
2016-2017	9	0,38	3,51
2016-2018	15	0,63	4,14
2016-2019	109	4,55	8,69
2017	8	0,33	9,02
2017-2018	82	3,43	12,45
2017-2019	446	18,63	31,08
2018	18	0,75	31,83
2018-2019	389	16,25	48,08
2019	1,243	51,92	100

Table C5: TimeFrame Distribution Female Employment

FundCategory Distribution			
FundCategory	*Observations*	*Percentage*	*Cumulative*
Financial institutions	1,728	72,18	72,18
High impact	306	12,78	84,96
Mezzanine finance	266	11,11	96,07
Pioneer funds	51	2,13	98,2
Private equity	43	1,8	100

Table C6: FundCategory Distribution Female Employment

InvestmentInstrument Distribution			
InvestmentInstrument	*Observations*	*Percentage*	*Cumulative*
Debt	2,261	94,44	94,44
Debt & Equity	24	1	95,45
Equity	90	3,76	99,21
Quasi-equity	15	0,63	99,83
Unspecified	4	0,17	100

Table C7: InvestmentInstrument Distribution Female Employment

Correlogram Variables Hypothesis 1.1.

	EmpChange_F	TCI_Log	CIDGGF_Log	TIP_Log	P_Emp_F	EmplChange	PriorRev_Log	NewRev_Log	PriorProf_Log	NewProf_Log	Pop_F	School_F	School_T	SecEdu_F	SecEdu_T	EM	SP	PSI	PSMI	GDPpC_Log
EmpChange_F	1,0000																			
TCI_Log	0,1083	1,0000																		
CIDGGF_Log	0,1216	0,9738	1,0000																	
TIP_Log	0,0148	0,2985	0,2335	1,0000																
P_Emp_F	0,6344	0,3022	0,2876	0,0676	1,0000															
EmplChange	0,8564	0,1972	0,1887	0,0964	0,7478	1,0000														
PriorRev_Log	0,0371	0,3855	0,3169	0,3170	0,1503	0,0970	1,0000													
NewRev_Log	0,0488	0,5079	0,4723	0,0030	0,1914	0,1307	0,4755	1,0000												
PriorProf_Log	0,7274	0,0585	0,0563	0,0352	0,8061	0,7884	0,0205	0,0320	1,0000											
NewProf_Log	0,0465	0,0518	0,0595	0,0117	0,0105	0,0809	0,0155	0,0329	0,0230	1,0000										
Pop_F	0,0351	0,0112	0,0273	0,0459	0,0116	0,0291	0,1341	0,0017	0,0288	0,0020	1,0000									
School_F	0,0160	0,0796	0,0789	0,0635	0,0008	0,0004	0,0318	0,0414	0,0097	0,0078	0,3256	1,0000								
School_T	0,0201	0,1112	0,1104	0,0856	0,0079	0,0063	0,0285	0,0641	0,0139	0,0056	0,3900	0,9920	1,0000							
SecEdu_F	0,0172	0,1858	0,1441	0,2454	0,0718	0,0502	0,0749	0,0833	0,0077	0,0031	0,3465	0,2904	0,3117	1,0000						
SecEdu_T	0,0201	0,0164	0,0381	0,1686	0,0332	0,0349	0,0538	0,0624	0,0087	0,0092	0,2067	0,2358	0,2320	0,4665	1,0000					
EM	0,0170	0,0811	0,0608	0,0766	0,0054	0,0042	0,1659	0,0257	0,0323	0,0066	0,7422	0,0078	0,0957	0,0276	0,1964	1,0000				
SP	0,0290	0,2767	0,2342	0,1696	0,0829	0,0616	0,0595	0,1714	0,0178	0,0271	0,2451	0,1039	0,0351	0,1551	0,0610	0,3635	1,0000			
PSI	0,0400	0,1626	0,1278	0,1932	0,0264	0,0488	0,0147	0,1184	0,0261	0,0052	0,8152	0,3839	0,4554	0,4413	0,2175	0,5732	0,1942	1,0000		
PSMI	0,0114	0,1248	0,1337	0,0082	0,0563	0,0140	0,0678	0,0663	0,0020	0,0204	0,3713	0,4633	0,4407	0,4116	0,3121	0,0082	0,6364	0,5631	1,0000	
GDPpC_Log	0,0469	0,0270	0,0249	0,1562	0,0267	0,0497	0,0674	0,0100	0,0261	0,0132	0,4871	0,5653	0,5707	0,5520	0,7368	0,0102	0,0896	0,5836	0,6406	1,0000

Table C8: Correlogram of Variables included in Multivariate Regressions for Hypothesis 1.1.

Residual Values vs. Predicted Values Plots – Female Employment

Table 21 Model (1)

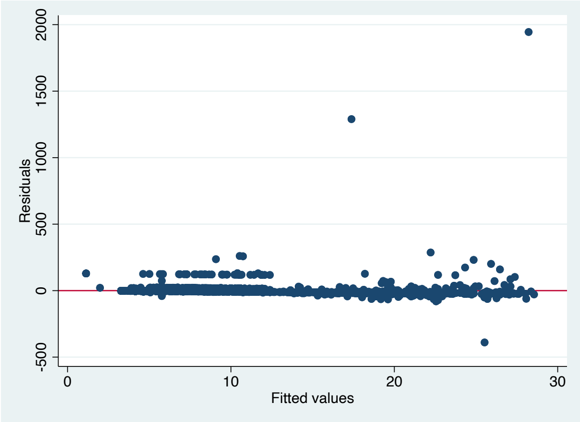


Table 21 Model (2)

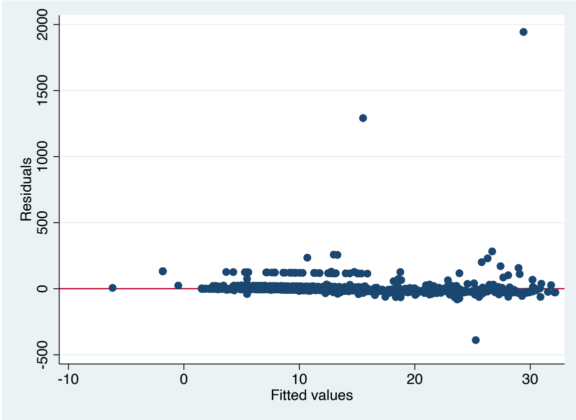


Table 22 Model (1)

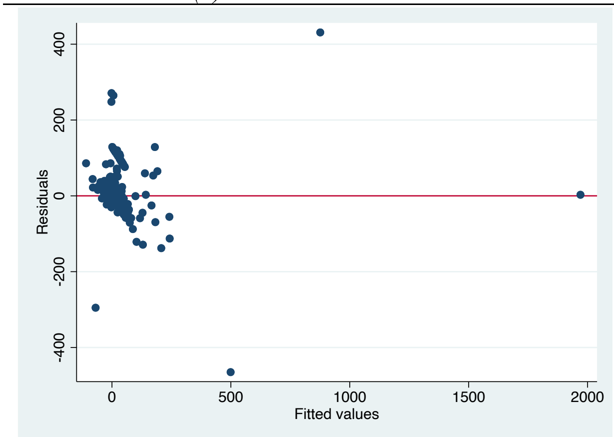


Table 22 Model (2)

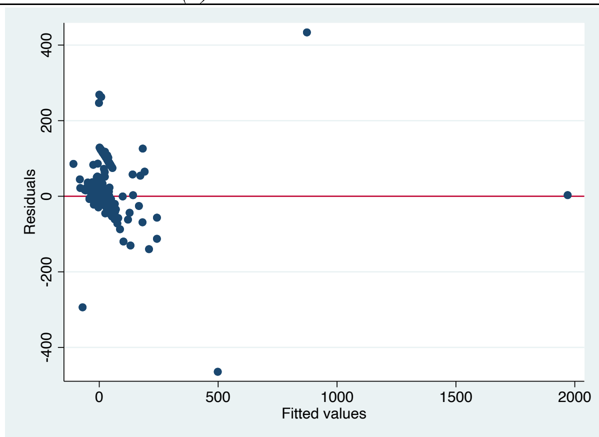


Table 22 Model (3)

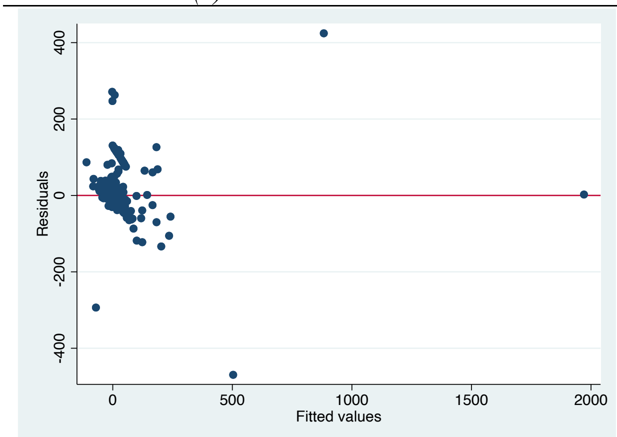


Table 22 Model (4)

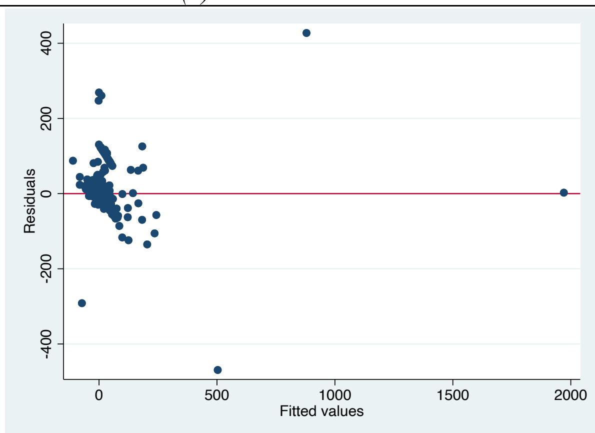


Table C9: Residual Values vs. Predicted Values Plots – Female Employment

Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Female Employment			
Variables: Fitted values of EmploymentChange_F. Ho = Constant Variance			
Table 21 Model (1)		*Table 21 Model (2)*	
Chi-Squared (1)	6095,57	Chi-Squared (1)	5204,87
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 22 Model (1)		*Table 22 Model (2)*	
Chi-Squared (1)	15322,62	Chi-Squared (1)	15633,73
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 22 Model (3)		*Table 22 Model (4)*	
Chi-Squared (1)	15363,01	Chi-Squared (1)	15726,58
Prob > chi2	0,0000	Prob > chi2	0,0000

Table C10: Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Female Employment

Kruskal-Wallis Test (Country)

Country	*Observations*	*Rank Sum*
Afghanistan	3	3.013
Armenia	514	759.949
Bangladesh	3	3.428
Cambodia	9	15.262
Cameroon	1	556
Colombia	1	1.857
Côte D'Ivoire	11	6.823
Côte d'Ivoire	1	24
Democratic Republic of the Congo	18	19.079
Egypt	22	21.374
Ethiopia	4	62.424
Georgia	17	28.254
Ghana	27	24.248
India	20	29.561
Indonesia	8	12.102
Jordan	39	37.378
Kenya	51	59.954
Lao People's Democratic Republic	3	2.197
Madagascar	1	556
Mauritius	2	2.486
Moldova	202	313.162
Myanmar	874	577.245
Nepal	8	15.797
Nigeria	35	41.030
Peru	2	4.615
Philippines	5	8.693
Rwanda	22	28.587
Senegal	4	1.214
South Africa	26	21.999
South Sudan	7	14.205
Sri Lanka	152	222.513
Tanzania	247	530.498
Uganda	37	39.970
United Arab Emirates	1	1.985
Vietnam	2	4.606
Zambia	15	6.359

Chi-Squared	*Degrees of Freedom*	*Probability*
(1) 1269.244	35	0,0001
(2) 1317.911	35	0,0001

Table C11: Kruskal-Wallis Equality-of-Populations Rank Test (Country) – Employment_F

Kruskal-Wallis Test (Sector)		
Sector	*Observations*	*Rank Sum*
Accommodation & Food	44	69.654,0
Administrative & Support	3	6.728,5
Agri, Food & Fish	849	1.300.000,0
Construction	15	20.340,0
Education	35	44.744,5
Electricity, Gas, Steam & AC Supply	12	16.262,0
Financial Services	11	14.194,5
Health & Social Work	52	63.641,0
Information & Communication	17	24.531,5
Manufacturing	187	236.834,0
Mining & Quarrying	4	5.831,0
Other Services	289	351.199,5
Real Estate	4	5.514,5
Science & Technique	11	9.486,0
Transportation & Storage	17	17.368,5
Water Supply	7	7.993,0
Wholesale & Retail	837	670.570,5
Chi-Squared	*Degrees of Freedom*	*Probability*
(1) 507,241	16	0,0001
(2) 526,690	16	0,0001

Table C12: Kruskal-Wallis Equality-of-Populations Rank Test (Sector) – Employment_F

Europe vs. Sub-Saharan Africa						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Europe	733	4,9387	0,7922766	21,45007	3,38334	6,49415
Sub-Saharan Africa	509	30,0741	4,9883220	112,54170	20,27384	39,8744
Combined	1242	15,2398	2,125106	74,89302	11,0706	19,40899
Difference		-25,13538	5,050847		-35,05736	-15,2134
Diff = Mean (Europe) – Mean (Sub-Saharan Africa)				**T – Stat**	**Satterthwaite's DoF**	
				-4,9765	533,717	
		Ho: diff = 0				
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 0.0000			Pr (T > t) = 0.0000		Pr (T > t) = 1.0000	

Table C13: Independent – T Test (Unequal Variances) Europe vs. Sub-Saharan Africa – Employment_F

South East Asia vs. Sub-Saharan Africa						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
South-East Asia	901	1,300476	0,3852602	11,56423	0,5443628	2,056589
Sub-Saharan Africa	509	30,07412	4,988322	112,54170	20,27384	39,8744
Combined	1410	11,68756	1,85331	69,59164	8,05202	15,32310
Difference		-28,77365	5,00318		-38,60283	-18,94446
Diff = Mean (South East Asia) – Mean (Sub-Saharan Africa)				**T – Stat**	**Satterthwaite's DoF**	
				-5,7511	514,068	
	Ho: diff = 0					
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 0.0000			Pr (T > t) = 0.0000		Pr (T > t) = 1.0000	

Table C14: Independent – T Test (Unequal Variances) South East Asia vs. Sub-Saharan Africa – Employment_F

Europe vs. South East Asia						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Europe	733	4,938745	0,79227660	21,45007	3,38334	6,49415
South-East Asia	901	1,300476	0,38526020	11,56423	0,5443628	2,056589
Combined	1634	2,932576	0,4163317	16,82928	2,115976	3,749176
Difference		3,638269	0,880981		1,909624	5,366915
Diff = Mean (Europe) – Mean (South East Asia)				**T – Stat**	**Satterthwaite's DoF**	
				4,1298	1.070,42	
	Ho: diff = 0					
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 1.0000			Pr (T > t) = 0.0000		Pr (T > t) = 0.0000	

Table C15: Independent – T Test (Unequal Variances) Europe vs. South East Asia – Employment_F

Agri, Food & Fish vs. Wholesale & Retail						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Agri, Food & Fish	849	5,763948	0,3670617	10,6953	5,043492	6,484404
Wholesale & Retail	837	1,840295	0,3633728	10,5127	1,127065	2,553526
Combined	1,686	3,816085	0,2625851	10,7820	3,301058	4,331112
Difference		3,923653	0,5165018		2,910600	4,936706
Diff = Mean (Agri, Food & Fish) – Mean (Wholesale & Retail)				**T – Stat**	**Satterthwaite's DoF**	
				7,5966	1.683,99	
	H0: Diff = 0					
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 1.0000			Pr (T > t) = 0.0000		Pr (T > t) = 0.0000	

Table C16: Independent Sample – T Test (Unequal Variances) Agri, Food & Fish vs. Wholesale & Retail – Employment_F

Active Portfolio vs. Exit Portfolio						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	2080	9,142427	1,278553	58,31098	6,63505	11,6498
1	314	7,25641	1,387932	24,59422	4,52555	9,987267
Combined	2394	8,895055	1,125674	55,07754	6,687658	11,10245
Diff		1,886016	1,887075		-1,817228	5,589261
Diff = Mean (0) – Mean (1)				**T – Stat**	**Satterthwaite's DoF**	
				0,9994	964,996	
Ho: diff = 0						
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 0,8411			Pr (T > t) = 0,3178		Pr (T > t) = 0,1589	

Table C17: Independent Sample - T Test (Unequal Variances) Active Portfolio vs. Exit Portfolio – Employment_F

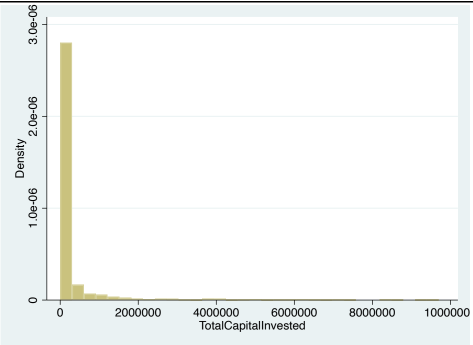
NonFemaleSME vs. Female SME						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	1561	10,51113	1,126224	44,49652	8,302059	12,7202
1	833	5,866609	2,449634	70,7007	1,05842	10,6748
Combined	2394	8,895055	1,125674	55,07754	6,687658	11,10245
Diff		4,644521	2,696124		-0,6451543	9,934197
Diff = Mean (0) – Mean (1)				**T-Stat**	**Satterthwaite's DoF**	
				1,7227	1192,48	
Ho: diff = 0						
Ha: diff < 0			*Ha: diff! =0*		*Ha: diff > 0*	
Pr (T < t) = 0.9574			Pr (T > t) = 0,0852		Pr (T > t) = 0,0426	

Table C18: Independent Sample - T Test (Unequal Variances) NonFemale SME vs. Female SME – Employment_F

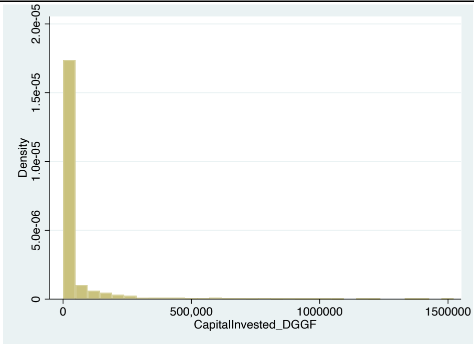
8.4. APPENDIX D: Youth Employment 18 – 24 Figures & Data Tables

Histograms Youth Employment 18 – 24 Dataset

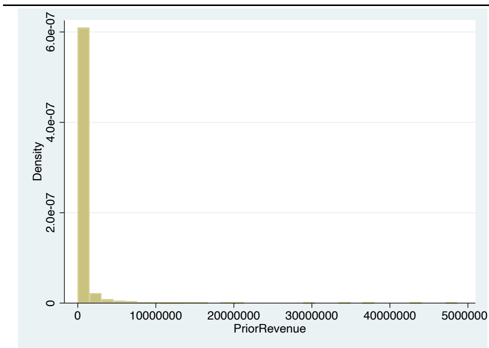
TotalCapitalInvested



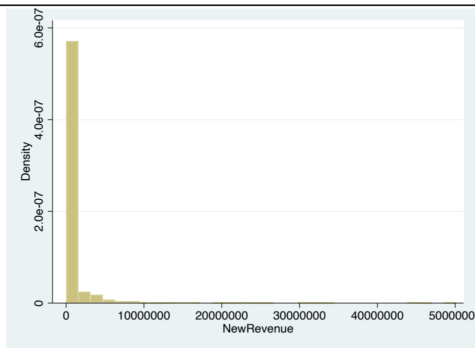
Capital Invested DGGF



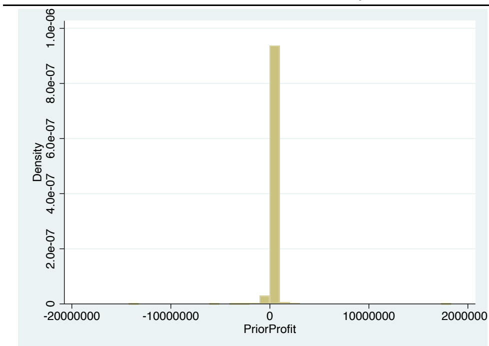
PriorRevenue



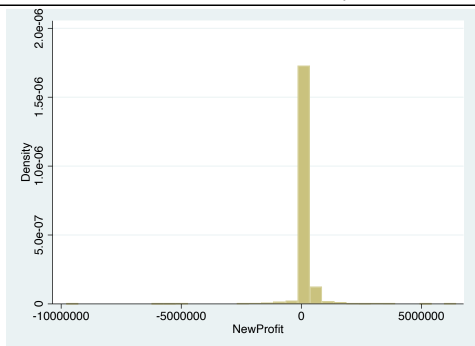
NewRevenue



PriorProfit



NewProfit



TimeinPortfolio

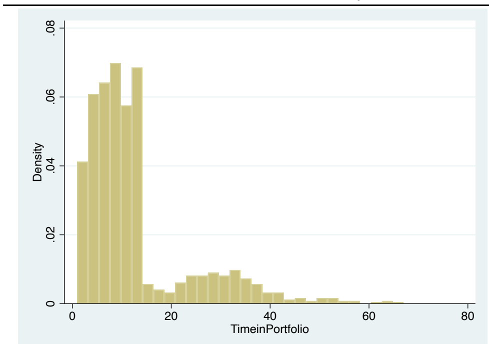


Figure D1: Histograms Youth Employment 18 – 24 Dataset

Descriptive Statistics Youth Employment 18 -24 Dataset

Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
TotalCapitalInvested_Log	1.736	9,90	1,94	7,38	16,09
CapitalInvestedDGGF_Log	1.736	9,58	1,35	6,51	14,24
TimeinPorftolio	1.736	13,88	12,41	1	70
TimeinPortfolio_Log	1.736	2,28	0,86	0	4,25
YouthSME	1.736	0,23	0,42	0	1
Exited Portfolio	1.736	0,07	0,26	0	1
PriorEmployment	1.736	20	8	0	2.342
NewEmployment	1.736	28	172	0	5.588
EmploymentChange	1.736	8	95	-228	3.246
PriorEmployment_Y18_24	1.736	6	14	0	357
NewEmployment_Y18_24	1.736	8	25	0	830
EmploymentChange_Y18_24	1.736	3	14	-62	473
Training	1.736	0,56	0,50	0	1
EMIndex	1.736	3,50	0,29	2,42	4
SPIndex	1.736	2,92	0,34	2,25	3,29
PSIIndex	1.736	3,50	0,23	2,64	3,90
PSMIIndex	1.736	3,09	0,25	2,25	3,32
Population_Log	1.736	16,68	0,98	14,81	19,39
SchoolEnrol_T	1.736	1,04	0,05	0,81	1,12
SecEdu_T	1.736	0,07	0,01	0,03	0,14
PriorRevenue_Log	1.736	8,63	4,42	-0,49	17,70
NewRevenue_Log	1.736	1,01	3,78	-0,80	17,73
PriorProfit_Log	1.736	16,47	0,40	0,01	17,30
NewProfit_Log	1.736	16,09	0,38	0,37	16,60
GDPpC_Log	1.736	8,50	0,90	6,35	10,00

Table D1 – Descriptive Statistics Dataset Youth Employment 18 – 24

Country Distribution			
Country	*Observations*	*Percentage*	*Cumulative*
Afghanistan	3	0,17	0,17
Armenia	113	6,51	6,68
Bangladesh	3	0,17	6,85
Cambodia	9	0,52	7,37
Cameroon	1	0,06	7,43
Côte D'Ivoire	10	0,58	8,01
Côte d'Ivoire	1	0,06	8,06
Democratic Republic of the Congo	18	1,04	9,1
Ethiopia	4	0,23	9,33
Georgia	17	0,98	10,31
Ghana	26	1,5	11,81
India	19	1,09	12,9
Indonesia	8	0,46	13,36
Kenya	48	2,76	16,13
Lao People's Democratic Republic	3	0,17	16,3
Madagascar	1	0,06	16,36
Mauritius	2	0,12	16,47
Moldova	41	2,36	18,84
Myanmar	874	50,35	69,18
Nepal	8	0,46	69,64
Nigeria	28	1,61	71,26
Philippines	5	0,29	71,54
Rwanda	20	1,15	72,7
Senegal	3	0,17	72,87
South Africa	22	1,27	74,14
South Sudan	7	0,4	74,54
Sri Lanka	151	8,7	83,24
Tanzania	244	14,06	97,29
Uganda	33	1,9	99,19
Vietnam	2	0,12	99,31
Zambia	12	0,69	100

Table D2: Country Distribution Youth Employment 18 – 24

Region Distribution			
Region	*Observations*	*Percentage*	*Cumulative*
Europe	171	9,85	9,85
South Asia	184	10,6	20,45
South-East Asia	901	51,9	72,35
Sub-Saharan Africa	480	27,65	100

Table D3: Region Distribution Youth Employment 18 – 24

Sector Distribution			
PrimarySector	*Observations*	*Percentage*	*Cumulative*
Accommodation & Food	39	2,25	2,25
Administrative & Support	1	0,06	2,3
Agri, Food & Fish	292	16,82	19,12
Construction	11	0,63	19,76
Education	29	1,67	21,43
Electricity, Gas, Steam & AC Supply	6	0,35	21,77
Financial Services	10	0,58	22,35
Health & Social Work	42	2,42	24,77
Information & Communication	16	0,92	25,69
Manufacturing	160	9,22	34,91
Other Services	283	16,3	51,21
Real Estate	4	0,23	51,44
Science & Technique	1	0,06	51,5
Transportation & Storage	16	0,92	52,42
Water Supply	5	0,29	52,71
Wholesale & Retail	821	47,29	100

Table D4: Sector Distribution Youth Employment 18 – 24

TimeFrame Distribution			
TimeFrame	**Freq.**	**Percent**	**Cum.**
2014-2018	1	0,06	0,06
2014-2019	10	0,58	0,63
2015-2018	5	0,29	0,92
2015-2019	39	2,25	3,17
2016	2	0,12	3,28
2016-2017	7	0,4	3,69
2016-2018	13	0,75	4,44
2016-2019	90	5,18	9,62
2017	1	0,06	9,68
2017-2018	17	0,98	10,66
2017-2019	200	11,52	22,18
2018	2	0,12	22,29
2018-2019	207	11,92	34,22
2019	1,142	65,78	100

Table D5: TimeFrame Distribution Youth Employment 18 – 24

FundCategory Distribution			
FundCategory	*Observations*	*Percentage*	*Cumulative*
Financial institutions	1,165	67,11	67,11
High impact	266	15,32	82,43
Mezzanine finance	217	12,5	94,93
Pioneer funds	45	2,59	97,52
Private equity	43	2,48	100

Table D6: FundCategory Distribution Youth Employment 18 – 24

InvestmentInstrument Distribution			
InvestmentInstrument	*Observations*	*Percentage*	*Cumulative*
Debt	1610	92,74	92,74
Debt & Equity	24	1,38	94,12
Equity	83	4,78	98,91
Quasi-equity	15	0,86	99,77
Unspecified	4	0,23	100

Table D7: InvestmentInstrument Distribution Youth Employment 18 – 24

Correlogram Variables Hypothesis 1.2.

	Emp_Y1824	TCI_Log	CIDGGF_Log	TIP_Log	P_Emp_Y1824	Empl_Change	PriorRev_Log	NewRev_Log	PriorProf_Log	NewProf_Log	Pop_Log	School_T	SecEdu_T	EMIndex	SPIndex	PSIIndex	PSMIIndex	GDPpC_Log
Emp_Y1824	1,0000																	
TCI_Log	0,1450	1,0000																
CIDGGF_Log	0,1694	0,9779	1,0000															
TIP_Log	0,0128	0,4160	0,3641	1,0000														
P_Emp_Y1824	0,6493	0,2757	0,3007	0,0497	1,0000													
Empl_Change	0,1353	0,2037	0,1989	0,1157	0,1428	1,0000												
PriorRev_Log	0,0481	0,3489	0,2665	0,3170	0,0481	0,1012	1,0000											
NewRev_Log	0,0463	0,4559	0,4153	0,0046	0,0867	0,1294	0,4441	1,0000										
PriorProf_Log	0,0057	0,0694	0,0679	0,0470	0,0126	0,8155	0,0264	0,0374	1,0000									
NewProf_Log	0,0004	0,0643	0,0658	0,0374	0,0154	0,8078	0,0128	0,0241	0,9896	1,0000								
Pop_Log	0,0563	0,3146	0,2934	0,2218	0,0136	0,0709	0,0073	0,1803	0,0318	0,0209	1,0000							
School_T	0,0166	0,1468	0,1518	0,0806	0,0383	0,0076	0,0466	0,0845	0,0170	0,0114	0,6903	1,0000						
SecEdu_T	0,0526	0,1016	0,0911	0,1371	0,0115	0,0410	0,0292	0,0315	0,0116	0,0180	0,5639	0,4097	1,0000					
EMIndex	0,0525	0,0710	0,0406	0,1513	0,0470	0,0087	0,2274	0,0128	0,0405	0,0523	0,1297	0,0247	0,2681	1,0000				
SPIndex	0,0615	0,3351	0,3131	0,1395	0,0880	0,0674	0,0343	0,1933	0,0232	0,0144	0,2132	0,1533	0,2261	0,3659	1,0000			
PSIIndex	0,0593	0,1920	0,1759	0,1537	0,0293	0,0556	0,0714	0,1331	0,0348	0,0272	0,7656	0,4727	0,2363	0,4762	0,0871	1,0000		
PSMIIndex	0,0283	0,1727	0,1767	0,0025	0,0833	0,0248	0,0600	0,0703	0,0009	0,0012	0,4070	0,4897	0,4132	0,1061	0,7198	0,5754	1,0000	
GDPpC_Log	0,0187	0,0659	0,0520	0,1171	0,0183	0,0496	0,0521	0,0240	0,0314	0,0308	0,7478	0,6634	0,7512	0,1092	0,2653	0,5920	0,7009	1,0000

Table D8: Correlogram of Variables included in Multivariate Regressions for Hypothesis 1.2.

Residual Values vs. Predicted Values Plots – Youth Employment 18 – 24

Table 25 Model (1)

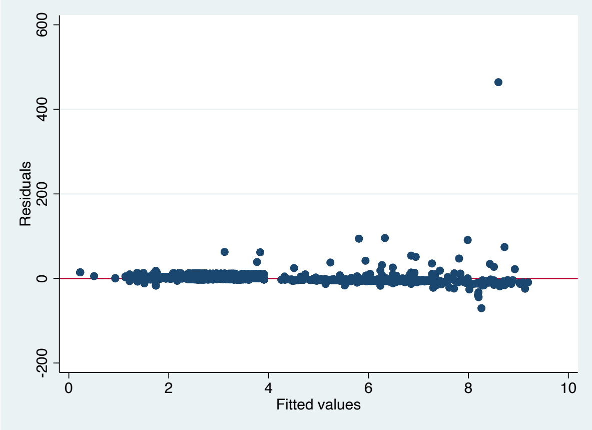


Table 25 Model (2)

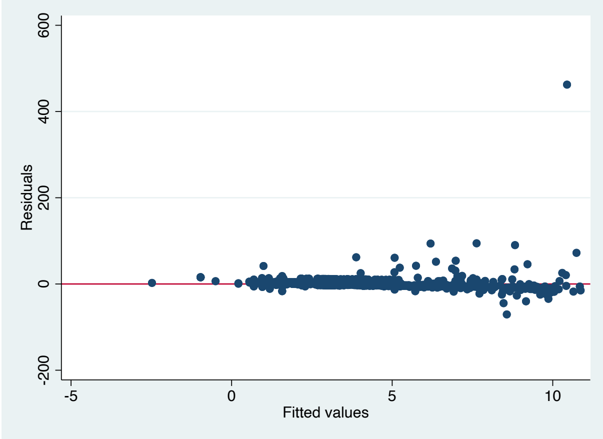


Table 26 Model (1)

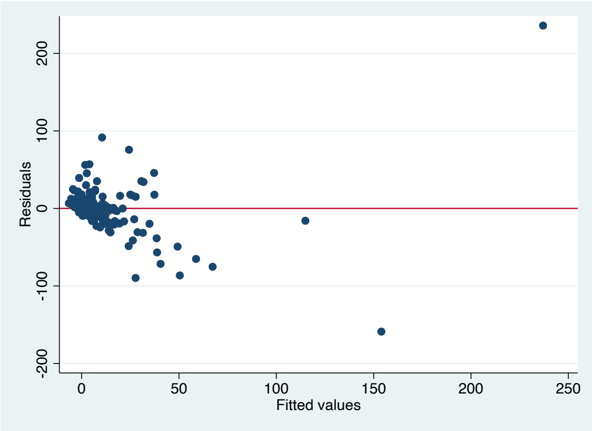


Table 26 Model (2)

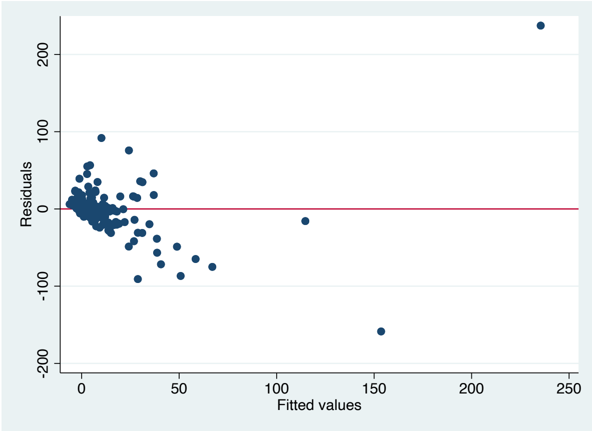


Table 26 Model (3)

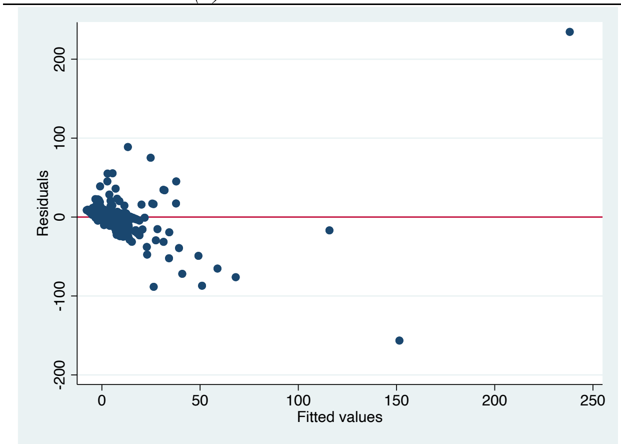


Table 26 Model (4)

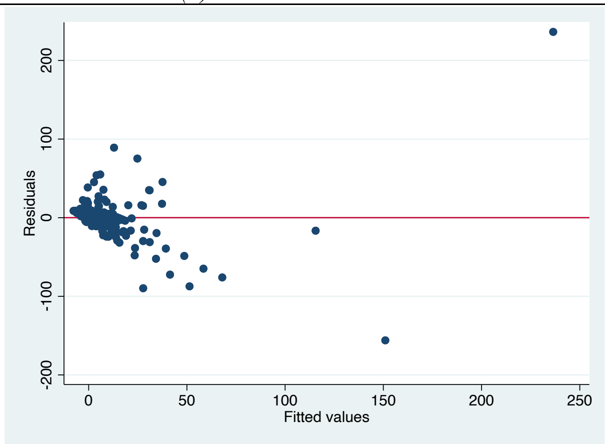


Table D9: Residual Values vs. Predicted Values Plots – Youth Employment 18 – 24

Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Youth Employment 18 - 24			
Variables: Fitted values of EmploymentChange_Y18 _24. Ho = Constant Variance			
Table 25 Model (1)		*Table 25 Model (2)*	
Chi-Squared (1)	5187,82	Chi-Squared (1)	6383,10
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 26 Model (1)		*Table 26 Model (2)*	
Chi-Squared (1)	112093,73	Chi-Squared (1)	112788,79
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 26 Model (3)		*Table 26 Model (4)*	
Chi-Squared (1)	110027,11	Chi-Squared (1)	110819,47
Prob > chi2	0,0000	Prob > chi2	0,0000

Table D10: Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Youth Employment 18 - 24

Kruskal-Wallis Test (Country)		
Country	*Observations*	*Rank Sum*
Afghanistan	3	2.304,5
Armenia	113	132.484,0
Bangladesh	3	1.329,5
Cambodia	9	8.448,0
Cameroon	1	498,5
Côte D'Ivoire	10	10.731,0
Côte d'Ivoire	1	1.713,0
Democratic Republic of the Congo	18	13.466,5
Ethiopia	4	4.019,0
Georgia	17	12.225,0
Ghana	26	30.114,5
India	19	14.331,0
Indonesia	8	8.015,0
Kenya	48	49.410,0
Lao People's Democratic Republic	3	1.287,0
Madagascar	1	42,0
Mauritius	2	1.277,0
Moldova	41	47.481,5
Myanmar	874	478.495,0
Nepal	8	12.345,0
Nigeria	28	21.603,0
Philippines	5	5.292,5
Rwanda	20	22.617,0
Senegal	3	3.594,0
South Africa	22	24.175,0
South Sudan	7	7.452,0
Sri Lanka	151	179.738,5
Tanzania	244	360.848,0
Uganda	33	35.542,0
Vietnam	2	3.293,5
Zambia	12	13.543,50

Chi-Squared	*Degrees of Freedom*	*Probability*
(1) 911,148	30	0,0001
(2) 987,715	30	0,0001

Table D11: Kruskal-Wallis Equality-of-Populations Rank Test (Country) – Employment_Y18_24

Kruskal-Wallis Test (Sector)		
Sector	*Observations*	*Rank Sum*
Accommodation & Food	39	44.241,00
Administrative & Support	1	5,00
Agri, Food & Fish	292	319.578,50
Construction	11	10.634,50
Education	29	33.211,50
Electricity, Gas, Steam & AC Supply	6	4.885,00
Financial Services	10	11.958,50
Health & Social Work	42	39.481,50
Information & Communication	16	21.750,50
Manufacturing	160	161.348,50
Other Services	283	272.004,00
Real Estate	4	5.602,50
Science & Technique	1	26,00
Transportation & Storage	16	18.121,50
Water Supply	5	2.124,00
Wholesale & Retail	821	562.743,50

Chi-Squared	*Degrees of Freedom*	*Probability*
(1) 250,372	15	0,0001
(2) 271,411	15	0,0001

Table D12: Kruskal-Wallis Equality-of-Populations Rank Test (Sector) – Employment_Y18_24

South-East Asia vs. Sub-Saharan Africa						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
South-East Asia	901	0,4716732	0,2044403	6,136614	0,070438	0,872908
Sub-Saharan Africa	480	4,854168	0,3195152	7,000228	4,226343	5,481992
Combined	1.381	1,994915	0,1823635	6,776958	1,637176	2,352655
Difference		-4,382495	0,3793228		-5,126985	-3,638004

Difference = Mean (South-East Asia) – Mean (Sub-Saharan Africa)	**T – Stat**	**Satterthwaite's DoF**
	-11,5535	873,565
Ho: Diff = 0		
Ha: Diff < 0	*Ha: Diff! = 0*	*Ha: Diff > 0*
Pr (T>t) = 0.0000	Pr (T>t) = 0.0000	Pr (T>t) = 1.0000

Table D13: Independent Sample T-Test (Unequal Variances) South-East Asia vs. Sub-Saharan Africa – Employment_Y18_24

Agri, Food & Fish vs. Wholesale & Retail						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Agri, Food & Fish	292	3,167444	0,510428	8,722196	2,162846	4,172043
Wholesale & Retail	821	0,638634	0,120187	3,443727	0,402723	0,874544
Combined	1,113	1,302077	0,163883	5,467392	0,980523	1,623631
Difference		2,528811	0,524387		1,497175	3,560446
Difference = Mean (Agri, Food & Fish) – Mean (Wholesale & Retail)				**T – Stat**	**Satterthwaite's DoF**	
				4,8224	323,809	
	Ho: Diff = 0					
Ha: Diff < 0			*Ha: Diff! = 0*		*Ha: Diff > 0*	
Pr (T>t) = 1.0000			Pr (T>t) = 0.0000		Pr (T>t) = 0.0000	

Table D14: Independent Sample T-Test (Unequal Variances) Agri, Food & Fish vs. Wholesale & Retail – Employment_Y18_24

Active Portfolio vs. Exit Portfolio						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	1.610	2,809242	0,3559881	14,28395	2,110993	3,507491
1	126	2,995286	0,192908	2,165387	2,613497	3,377075
Combined	1.736	2,822745	0,330439	13,76787	2,174643	3,470846
Diff		-0,1860439	0,4048963		-0,9803794	0,6082917
Diff = Mean (0) – Mean (1)				**T-Stat**	**Satterthwaite's DoF**	
				-0,4595	1276,19	
	Ho: diff = 0					
Ha: diff < 0			*Ha: diff! = 0*		*Ha: diff > 0*	
Pr (T < t) = 0,3230			Pr (T > t) = 0,6460		Pr (T > t) = 0,6770	

Table D15: Independent Sample - T Test (Unequal Variances) Active Portfolio vs. Exit Portfolio – Employment_Y18_24

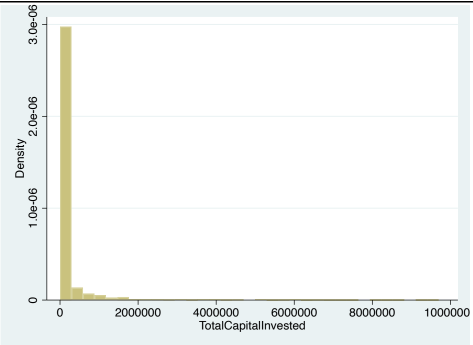
NonYouthSME vs. Youth SME						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	1.343	3,15385	0,4173268	15,29376	2,335164	3,972532
1	393	1,691266	0,3050269	6,046923	1,09157	2,290959
Combined	1.736	2,822745	0,3304394	13,76787	2,174643	3,470846
Diff		1,462582	0,5169169		0,4486758	2,476489
Diff = Mean (0) – Mean (1)				**T-Stat**	**Satterthwaite's DoF**	
				2,8294	1597,77	
	Ho: diff = 0					
Ha: diff < 0			*Ha: diff! = 0*		*Ha: diff > 0*	
Pr (T < t) = 0.9976			Pr (T > t) = 0,0047		Pr (T > t) = 0,024	

Table D16: Independent Sample - T Test (Unequal Variances) NonYouthSME vs. Youth SME – Employment_Y18_24

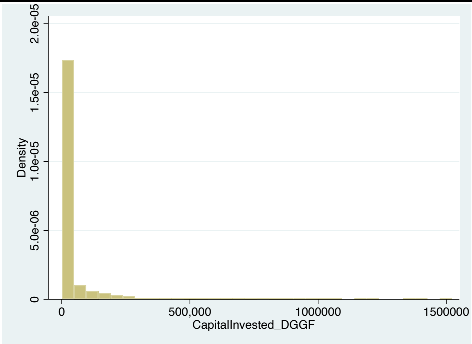
8.5. APPENDIX E: Youth Employment 25 – 35 Figures & Data Tables

Histograms Youth Employment 25 – 35 Dataset

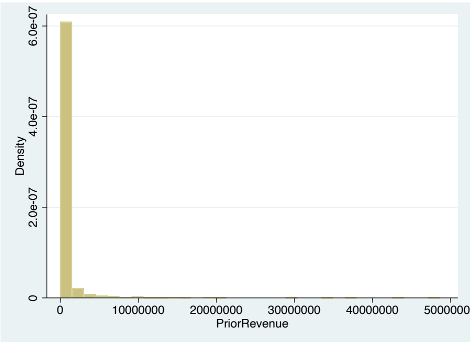
TotalCapitalInvested



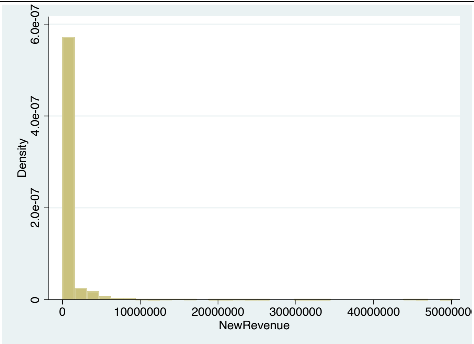
Capital Invested DGGF



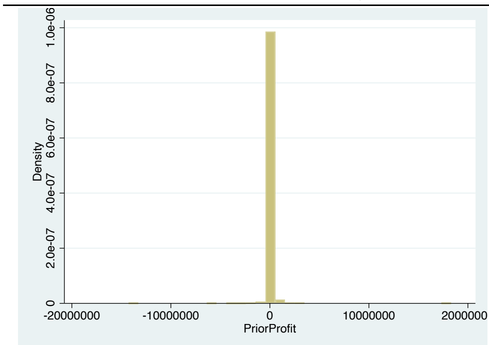
PriorRevenue



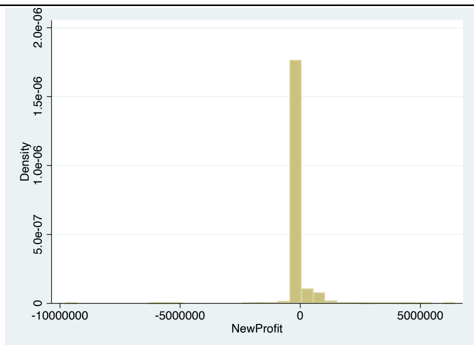
NewRevenue



PriorProfit



NewProfit



TimeinPortfolio

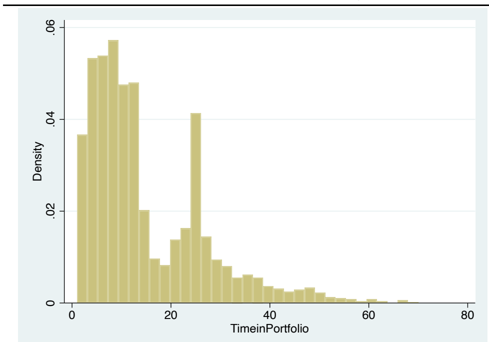


Figure E1: Histograms Youth Employment 25 – 35 Dataset

Descriptive Statistics Youth Employment 25 - 35 Dataset					
Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
TotalCapitalInvested_Log	2.325	9,75	1,83	7,38	16,09
CapitalInvestedDGGF_Log	2.325	9,49	1,32	6,51	14,24
TimeinPorftolio	2.325	15,01	11,68	1,00	70,00
TimeinPortfolio_Log	2.325	2,40	0,84	0	4,25
ExitedPortfolio	2.325	0,14	0,34	0	1
YouthSME	2.325	0,26	0,44	0	1
PriorEmployment	2.325	17	75	0	2.342
NewEmployment	2.325	24	152	0	5.588
EmploymentChange	2.325	7	84	-228	3.246
PriorEmployment_Y25_35	2.325	14	27	0	450
NewEmployment_Y25_35	2.325	19	75	0	2.900
EmploymentChange_Y25_35	2.325	5	68	-326	2.853
Training	2.325	0,42	0,49	0	1
EMIndex	2.325	3,51	0,30	2,42	4
SPIndex	2.325	2,91	0,33	2,25	3,29
PSIIndex	2.325	3,51	0,24	2,64	3,90
PSMIIndex	2.325	3,07	0,24	2,25	3,32
GDPpCGrowth	2.325	0,03	0,02	0,00	0,07
Population_Log	2.325	16,61	0,98	14,81	19,39
SchoolEnrol_T	2.325	1,04	0,05	0,81	1,12
SecEdu_T	2.325	0,07	0,01	0,03	0,14
PriorRevenue_Log	2.325	9,02	3,97	-0,49	17,70
NewRevenue_Log	2.325	10,12	3,45	-0,80	17,73
PriorProfit_Log	2.325	16,47	0,34	0,01	17,30
NewProfit_Log	2.325	16,09	0,33	0,37	16,60
GDPpC_Log	2.325	8,44	0,94	6,35	10,00

Table E1 - Descriptive Statistics Dataset Youth Employment 25 - 35

Country Distribution			
Country	*Observations*	*Percentage*	*Cumulative*
Afghanistan	3	0,13	0,13
Armenia	512	22,02	22,15
Bangladesh	3	0,13	22,28
Cambodia	9	0,39	22,67
Cameroon	1	0,04	22,71
Côte D'Ivoire	10	0,43	23,14
Côte d'Ivoire	1	0,04	23,18
Democratic Republic of the Congo	18	0,77	23,96
Egypt	19	0,82	24,77
Ethiopia	4	0,17	24,95
Georgia	17	0,73	25,68
Ghana	27	1,16	26,84
India	19	0,82	27,66
Indonesia	8	0,34	28
Kenya	49	2,11	30,11
Lao People's Democratic Republic	3	0,13	30,24
Madagascar	1	0,04	30,28
Mauritius	2	0,09	30,37
Moldova	201	8,65	39,01
Myanmar	874	37,59	76,6
Nepal	8	0,34	76,95
Nigeria	28	1,2	78,15
Philippines	5	0,22	78,37
Rwanda	21	0,9	79,27
Senegal	4	0,17	79,44
South Africa	24	1,03	80,47
South Sudan	7	0,3	80,77
Sri Lanka	151	6,49	87,27
Tanzania	245	10,54	97,81
Uganda	34	1,46	99,27
United Arab Emirates	1	0,04	99,31
Vietnam	2	0,09	99,4
Zambia	14	0,6	100

Table E2: Country Distribution Youth Employment 25 - 35

Region Distribution			
Region	*Observations*	*Percentage*	*Cumulative*
Europe	730	31,4	31,4
Middle East	20	0,86	32,26
South Asia	184	7,91	40,17
South-East Asia	901	38,75	78,92
Sub-Saharan Africa	490	21,08	100

Table E3: Region Distribution Youth Employment 25 – 35

Sector Distribution			
PrimarySector	*Observations*	*Percentage*	*Cumulative*
Accommodation & Food	42	1,81	1,81
Administrative & Support	3	0,13	1,94
Agri, Food & Fish	845	36,34	38,28
Construction	15	0,65	38,92
Education	30	1,29	40,22
Electricity, Gas, Steam & AC Supply	6	0,26	40,47
Financial Services	11	0,47	40,95
Health & Social Work	45	1,94	42,88
Information & Communication	17	0,73	43,61
Manufacturing	167	7,18	50,8
Other Services	288	12,39	63,18
Real Estate	4	0,17	63,35
Science & Technique	1	0,04	63,4
Transportation & Storage	16	0,69	64,09
Water Supply	5	0,22	64,3
Wholesale & Retail	830	35,7	100

Table E4: Sector Distribution Youth Employment 25 – 35

TimeFrame Distribution			
TimeFrame	*Observations*	*Percentage*	*Cumulative*
2014-2018	1	0,04	0,04
2014-2019	11	0,47	0,52
2015-2018	5	0,22	0,73
2015-2019	40	1,72	2,45
2016	2	0,09	2,54
2016-2017	8	0,34	2,88
2016-2018	15	0,65	3,53
2016-2019	94	4,04	7,57
2017	8	0,34	7,91
2017-2018	82	3,53	11,44
2017-2019	425	18,28	29,72
2018	18	0,77	30,49
2018-2019	385	16,56	47,05
2019	1,231	52,95	100

Table E5: TimeFrame Distribution Youth Employment 25 – 35

FundCategory Distribution			
FundCategory	*Observations*	*Percentage*	*Cumulative*
Financial institutions	1,724	74,15	74,15
High impact	266	11,44	85,59
Mezzanine finance	245	10,54	96,13
Pioneer funds	47	2,02	98,15
Private equity	43	1,85	100

Table E6: FundCategory Distribution Youth Employment 25 – 35

InvestmentInstrument Distribution			
InvestmentInstrument	*Observations*	*Percentage*	*Cumulative*
Debt	2,197	94,49	94,49
Debt & Equity	24	1,03	95,53
Equity	85	3,66	99,18
Quasi-equity	15	0,65	99,83
Unspecified	4	0,17	100

Table E7: InvestmentInstrument Distribution Youth Employment 25 – 35

Correlogram Variables Hypothesis 1.3.

	Emp_Y2535	TCI_Log	CIDGGF_Log	TIP_Log	P_Emp_Y2535	Empl_Change	PriorRev_Log	NewRev_Log	PriorProf_Log	NewProf_Log	Pop_Log	School_T	SecEdu_T	EMIndex	SPIndex	PSIIndex	PSMIIndex	GDPpC_Log
Emp_Y2535	1,0000																	
TCI_Log	0,0184	1,0000																
CIDGGF_Log	0,0299	0,9740	1,0000															
TIP_Log	0,0417	0,2694	0,2075	1,0000														
P_Emp_Y2535	0,0827	0,4784	0,4563	0,0036	1,0000													
Empl_Change	0,4018	0,2006	0,1890	0,0998	0,1388	1,0000												
PriorRev_Log	0,0398	0,3507	0,2838	0,2982	0,0370	0,0965	1,0000											
NewRev_Log	0,0446	0,4807	0,4472	0,0302	0,1216	0,1295	0,4559	1,0000										
PriorProf_Log	0,0023	0,0638	0,0604	0,0381	0,0290	0,7917	0,0228	0,0345	1,0000									
NewProf_Log	0,0101	0,0533	0,0534	0,0281	0,0246	0,7785	0,0065	0,0177	0,9888	1,0000								
Pop_Log	0,0136	0,2469	0,2207	0,2202	0,0980	0,0627	0,0417	0,1577	0,0253	0,0131	1,0000							
School_T	0,0009	0,1027	0,1035	0,0837	0,0106	0,0070	0,0404	0,0557	0,0142	0,0098	0,6453	1,0000						
SecEdu_T	0,0093	0,0063	0,0594	0,1600	0,0855	0,0334	0,0696	0,0799	0,0095	0,0138	0,4687	0,2466	1,0000					
EMIndex	0,0181	0,1058	0,0796	0,0834	0,0114	0,0042	0,1868	0,0429	0,0334	0,0469	0,2301	0,0652	0,2042	1,0000				
SPIndex	0,0004	0,2564	0,2159	0,1565	0,1421	0,0625	0,0378	0,1536	0,0192	0,0087	0,3037	0,0520	0,0690	0,3636	1,0000			
PSIIndex	0,0115	0,1258	0,0960	0,1786	0,1008	0,0496	0,0469	0,0915	0,0279	0,0194	0,7487	0,4402	0,2215	0,5716	0,1685	1,0000		
PSMIIndex	0,0212	0,1350	0,1428	0,0063	0,0371	0,0143	0,0717	0,0699	0,0019	0,0008	0,3584	0,4363	0,3224	0,0115	0,6518	0,5685	1,0000	
GDPpC_Log	0,0251	0,0035	0,0468	0,1464	0,0780	0,0490	0,0851	0,0251	0,0270	0,0245	0,6746	0,5756	0,7433	0,0148	0,1049	0,5838	0,6425	1,0000

Table E8: Correlogram of Variables included in Multivariate Regressions for Hypothesis 1.3.

Residual Values vs. Predicted Values Plots – Youth Employment 25 – 35

Table 29 Model (1)

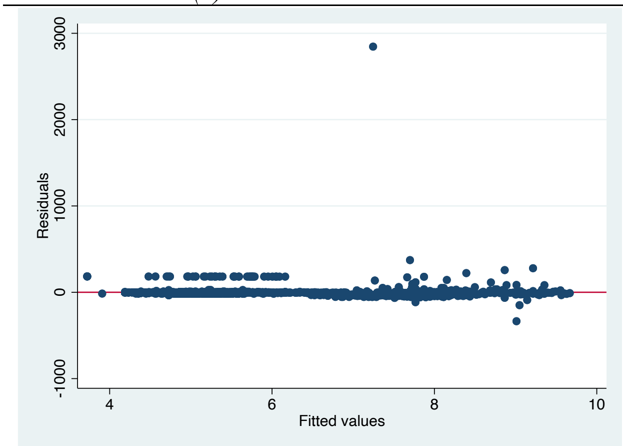


Table 29 Model (2)

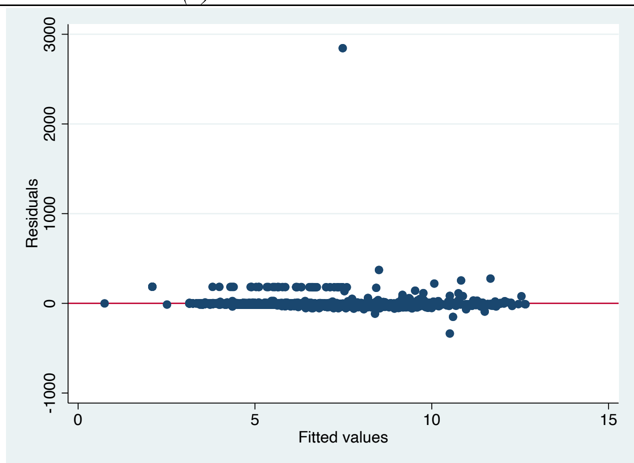


Table 30 Model (1)

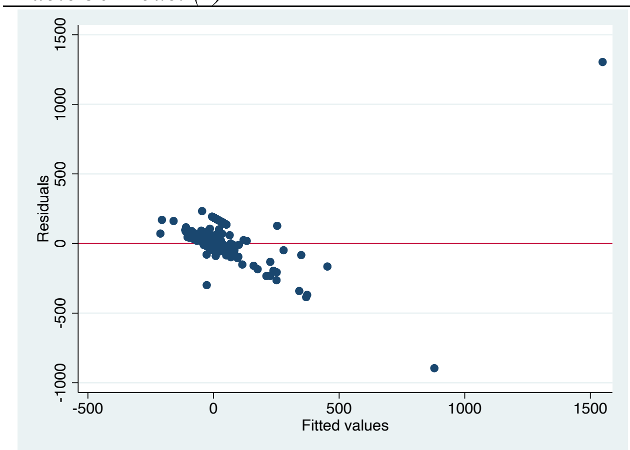


Table 30 Model (2)

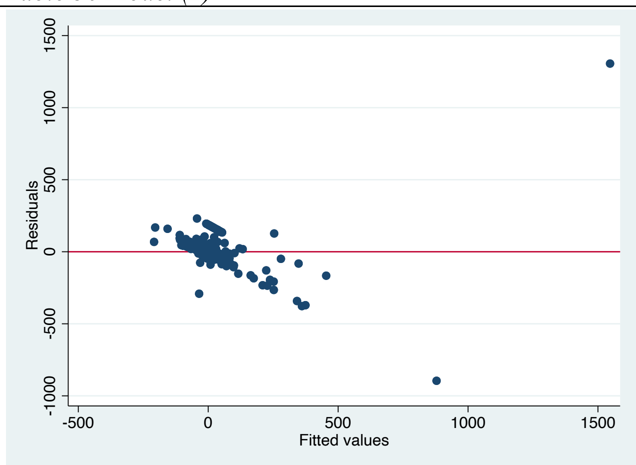


Table 30 Model (3)

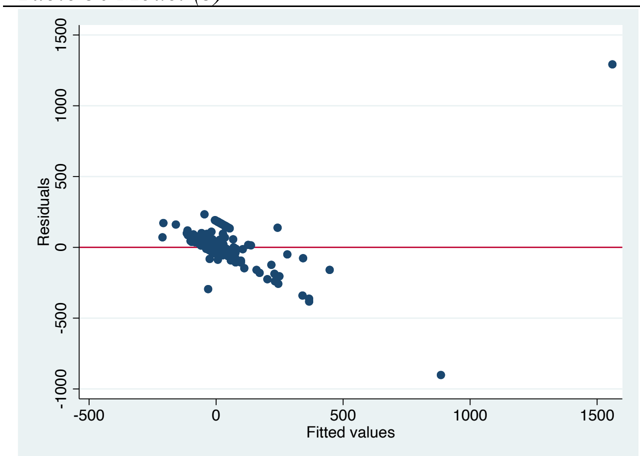


Table 30 Model (4)

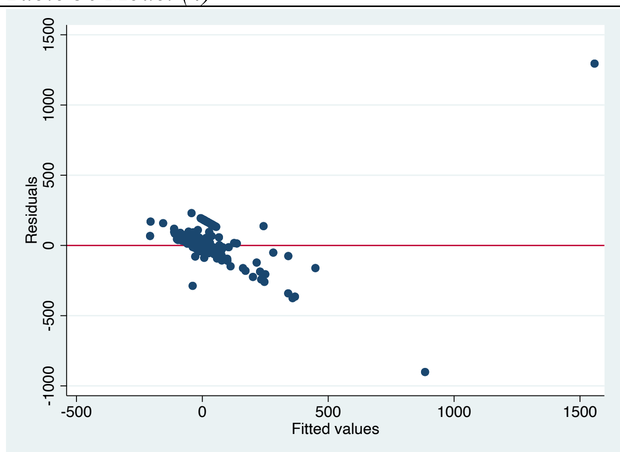


Table E9: Residual Values vs. Predicted Values Plots – Youth Employment 25 – 35

Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Youth Employment 25 - 35			
Variables: Fitted values of EmploymentChange_Y25_35. Ho = Constant Variance			
Table 29 Model (1)		*Table 29 Model (2)*	
Chi-Squared (1)	2065,98	Chi-Squared (1)	1125,81
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 30 Model (1)		*Table 30 Model (2)*	
Chi-Squared (1)	215264,38	Chi-Squared (1)	215428,22
Prob > chi2	0,0000	Prob > chi2	0,0000
Table 30 Model (3)		*Table 30 Model (4)*	
Chi-Squared (1)	213703,14	Chi-Squared (1)	213942,63
Prob > chi2	0,0000	Prob > chi2	0,0000

Table E10: Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity - Youth Employment 25 - 35

Kruskal-Wallis Test (Country)		
Country	*Observations*	*Rank Sum*
Afghanistan	3	3.445,5
Armenia	512	884.535,5
Bangladesh	3	4.473,0
Cambodia	9	11.880,0
Cameroon	1	780,5
Côte D'Ivoire	10	1.343,0
Côte d'Ivoire	1	161,0
Democratic Republic of the Congo	18	23.586,0
Egypt	19	10.039,0
Ethiopia	4	4.947,0
Georgia	17	22.284,0
Ghana	27	19.246,0
India	19	31.635,5
Indonesia	8	11.075,5
Kenya	49	33.499,5
Lao People's Democratic Republic	3	3.307,5
Madagascar	1	2.008,5
Mauritius	2	3.344,5
Moldova	201	336.290,0
Myanmar	874	782.281,5
Nepal	8	14.075,5
Nigeria	28	19.496,5
Philippines	5	2.086,5
Rwanda	21	12.479,5
Senegal	4	295,5
South Africa	24	3.925,0
South Sudan	7	11.401,0
Sri Lanka	151	155.036,0
Tanzania	245	256.067,0
Uganda	34	31.177,5
United Arab Emirates	1	172,0
Vietnam	2	4.457,0
Zambia	14	3.143,0
Chi-Squared	*Degrees of Freedom*	*Probability*
875,893	32	0,0001
897,716	32	0,0001

Table E11: Kruskal-Wallis Equality-of-Populations rank test (Country) – Employment_Y25_35

Kruskal-Wallis Test (Sector)		
Sector	*Observations*	*Rank Sum*
Accommodation & Food	42	58.095,5
Administrative & Support	3	2.272,5
Agri, Food & Fish	845	1.110.000,0
Construction	15	17.028,5
Education	30	22.572,5
Electricity, Gas, Steam & AC Supply	6	5.744,0
Financial Services	11	18.526,0
Health & Social Work	45	28.761,0
Information & Communication	17	15.471,5
Manufacturing	167	203.409,0
Other Services	288	307.624,0
Real Estate	4	4.233,5
Science & Technique	1	2.202,0
Transportation & Storage	16	17.280,0
Water Supply	5	5.870,0
Wholesale & Retail	830	887.495,0
Chi-Squared	*Degrees of Freedom*	*Probability*
120,467	15	0,0001
123,468	15	0,0001

Table E12: Kruskal-Wallis Equality-of-Populations rank test (Country) – Employment_Y25_35

Europe vs. Sub-Saharan Africa						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Europe	730	3,78424	0,20773	5,61243	3,37643	4,19205
Sub-Saharan Africa	490	17,5685	6,59905	1,46076	4,60254	30,53450
Combined	1.220	0,93205	2,65878	9,28673	4,10425	14,53685
Difference		-13,7843	6,60231		-2,67566	-0,81194

Diff = Mean (Europe) – Mean (South-East Asia)	**T-Stat**	**Satterthwaite's DoF**
	-2,0878	489,969
H0: Diff = 0		
Ha: diff < 0	*Ha: diff! = 0*	*Ha: diff > 0*
Pr (T < t) = 0.0187	Pr (|T| > |t|) = 0.0373	Pr (T > t) = 0.9813

Table E13: Independent T Test (Unequal Variances) Europe vs. Sub-Saharan Africa – Employment_Y25_35

Europe vs. South-East Asia						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Europe	730	3,784239	0,207725	5,612427	3,376428	4,192050
South-East Asia	901	0,8055007	0,3549998	1,0655910	0,1087769	1,5022250
Combined	1,631	2,138719	0,220053	8,886977	1,707103	2,570335
Difference		2,978738	0,411309		2,171899	3,785577
Diff = Mean (Europe) – Mean (South-East Asia)				**T-Stat**	**Satterthwaite's DoF**	
				7,2421	1.416,760	
	H0: Diff = 0					
	Ha: diff < 0			*Ha: diff! = 0*	*Ha: diff > 0*	
	Pr (T < t) = 1,0000			Pr (|T| > |t|) = 0,0000	Pr (T > t) = 0,0000	

Table E14: Independent T Test (Unequal Variances) Europe vs. South-East Asia – Employment_Y25_35

South-East Asia vs. Sub-Saharan Africa						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
South-East Asia	901	0,8055007	0,3549998	1,0655910	0,1087769	1,5022250
Sub-Saharan Africa	490	17,568520	6,5990450	1,4607610	4,6025380	30,5345000
Combined	1.391	6,7105190	2,3442790	8,7432490	2,1118120	11,3092300
Difference		-16,763020	6,608587		-29,747570	-3,778475
Diff = Mean (South-East Asia) – Mean (Sub-Saharan Africa)				**T-Stat**	**Satterthwaite's DoF**	
				-2,5366	491,832	
	H0: Diff = 0					
	Ha: diff < 0			*Ha: diff! = 0*	*Ha: diff > 0*	
	Pr (T < t) = 0,0058			Pr (|T| > |t|) = 0,0115	Pr (T > t) = 0,9942	

Table E15: Independent T Test (Unequal Variances) South-East Asia vs. Sub-Saharan Africa – Employment_Y25_35

Agri, Food & Fish vs. Wholesale & Retail						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
Agri, Food & Fish	845	-0,360738	0,309412	8,994262	-0,968045	0,246570
Wholesale & Retail	830	1,006364	0,494672	14,251370	0,035407	1,977321
Combined	1.675	0,316692	0,290993	11,909420	-0,254058	0,887441
Difference		-1,367102	0,583469		-2,511673	-0,222530
Diff = Mean (Agri, Food & Fish) – Mean (Wholesale & Retail)				**T-Stat**	**Satterthwaite's DoF**	
				-2,3431	1.394,85	
	H0: Diff = 0					
	Ha: diff < 0			*Ha: diff! = 0*	*Ha: diff > 0*	
	Pr (T < t) = 0.0096			Pr (|T| > |t|) = 0.0193	Pr (T > t) = 0.9904	

Table E16: Independent Sample T Test (Unequal Variances) Agri, Food & Fish vs. Wholesale & Retail – Employment_Y25_35

Active Portfolio vs. Exit Portfolio						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	2.012	5,945238	1,625157	72,89695	2,758071	9,132406
1	313	1,47155	0,5393512	9,542097	0,410325	2,532776
Combined	2.325	5,342974	1,408550	67,91781	2,580829	8,105119
Diff		4,473688	1,712319		1,115837	7,831539
	Diff = Mean (0) – Mean (1)			**T-Stat**	**Satterthwaite's DoF**	
				2,6126	2298,65	
	Ho: diff = 0					
	Ha: diff < 0		*Ha: diff! = 0*		*Ha: diff > 0*	
	Pr (T < t) = 0,9955		Pr (T > t) = 0,0090		Pr (T > t) = 0,0045	

Table E17: Independent Sample T Test (Unequal Variances) Active Portfolio vs. Exit Portfolio – Employment_Y25_35

NonYouthSME vs. Youth SME						
Group	*Observations*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Confidence Interval]*	
0	1,716	6,768979	1,883331	78,01629	3,075111	10,46285
1	609	1,324872	0,8515094	21,01348	-0,3473843	2,997129
Combined	2,325	5,342974	1,40855	67,91781	2,580829	8,105119
Diff		5,444106	2,066883		1,390887	9,497326
	Diff = Mean (0) – Mean (1)			**T-Stat**	**Satterthwaite's DoF**	
				2,6340	2225,51	
	Ho: diff = 0					
	Ha: diff < 0		*Ha: diff! = 0*		*Ha: diff > 0*	
	Pr (T < t) = 0.9958		Pr (T > t) = 0,0085		Pr (T > t) = 0,0042	

Table E18: Independent Sample T Test (Unequal Variances) NonYouthSME vs. Youth SME – Employment_Y25_35