Louvain School of Management

Risk and return of impact investing

Quantitative analysis of open-end impact funds in the USA and in Europe over the period 2014-2018

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1 INTRODUCTION

Impact investing brings the quest for a positive impact on the financial markets. Although long considered by many as irreconcilable, impact investing has positioned itself at the crossroad of philanthropy and financial performance (Bell, 2013; Chiappini, 2017; Höchstädter & Scheck, 2015; La Torre & Calderini, 2018; Höchstädter & Scheck, 2015). Financial investors are now offered with the chance of improving society. Moreover, the possibilities for non-profit organizations, charities, communities, social enterprises, and social businesses to raise their capital are tremendously opened. Henceforth, impact investing is considered as an opportunity for achieving the United Nations Sustainable Development Goals (GIIN, 2017a), thereby contributing to a better world, joining the worldwide battle for the planet, poverty, peace, and prosperity (United Nations Development Programme, n.d.).

On the impact investing field, the use of investment funds, called impact funds, is on the booming, growing at 16% computed annual growth rate (CAGR) on the 2014-2018 period. More and more financial institutions invest in funds and offer this solution to their clients. In 2018, the Global Impact Investing Network (GIIN), in its annual survey (GIIN, 2019a), found that nearly half of the actors of the impact investing market invested into funds, representing one-third of the assets under management (AUM) of the industry.

Another strong trend came from the retail investors whose investment into impact funds grew tremendously at a 21% CAGR during 2014-2018 as they have nowadays many opportunities of investing in impact funds. Retain investors thus became, in 2018, the second-largest contributor of impact funds in terms of AUM, reaching 16% of the total AUM (GIIN, 2019a).

While the impact investing investments thorough mutual funds by retail investors are booming, researches from academics do no keep up the pace. Although definitions of the concept of impact investing and its measurement start to ramp up, an extensive analysis of the subject is lacking. The returns and risks of impact funds, on a quantitative level, more specifically, have barely been studied. The researchers rather focused on private equity (Bouri, *et al.*, 2015; Gray, *et al.*, 2015), private debt (Castellas, Findlay and Addis, 2016; EngagedX-Social Investment Research Council, 2015; Symbiotics, 2017) and real assets (Castellas, *et al.*, 2016; Dithrich, *et al.*, 2017). From a risk perspective, the researches focused on the identification of the risks rather than quantifying them (Barby & Gan, 2014; Chappini, 2017).

Aimed at filling the blanks, this paper researched the financial performance and risks of the most invested mutual fund instrument, the open-end funds, by focusing on the two major markets where funds are domiciled, namely the United-States and Europe. As the impact investing field being is new, the thesis instigated the 2014-2018 period. Precisely, this thesis aimed at answering the following research question:

"What are the risks and return of open-end impact funds in the USA and Europe over the period 2014-2018?"

The research question drew upon several concepts and terms hereafter defined, more specifically the impact investing concept, the notion of impact and the instruments researched.

1. **(Social) impact investing**, or **SII**, the burgeoning concept of this paper, is not unanimously defined by academics and practitioners. Based on some of the most cited characteristics, an impact investment can be reasonably defined as an investment that intentionally aims to achieve both social and/or environmental impact as well as a financial return (Bugg-Levine & Emerson, 2011; Chiappini, 2017; Donner & Huang, 2019; La Torre & Calderini, 2018; Rodin & Brandenburg, 2014; World Economic Forum, 2013).
2. The notion of **social and/or environmental impacts** is itself a matter of debate among academics. One accredited definition of social impact is "*the portion of total outcome, which is directly linked to the social [and/or environmental] activity put in place above and beyond what have happened anyway*" (Chiappini, 2017, p. 36).
3. **Impact funds**, the instrument studied in the thesis, also called impact-oriented fund, are investment funds within the scope of impact investing, whose investments aim at generating both financial and measurable social and/or environmental impact.
4. From the different types of impact funds, the thesis focused on open-end(ed) fund, a type of mutual funds. **Mutual funds** are defined under the US law as "*legal entities which have no employees and are governed by a board of directors (or trustees) who are elected by the fund investors. Directors outsource all activities of the fund and are charged with acting in the best interests of the fund investors*" (Elton & Gruber, 2013, p. 1012) as established in the Investment Company Act of 1940.

5. **Open-ended funds** are the most important type of mutual funds in terms of AUM (Bloomberg, 2019; Elton & Gruber, 2013). Their prices are determined by the Net Asset Value per share, fixed at the end of the day. They can be bought anytime during trading hours. Open-end funds are often wrongfully called mutual funds while mutual funds are a wider term including open-end(ed) funds, closed-end(ed) funds as well as exchange-traded funds (Elton & Gruber, 2013).

The research question was addressed in the report by testing for two major hypotheses and by assuming no divergence compared to the market:

1. **The financial performance of open-end impact funds is aligned with the market.**
2. **The volatility of open-end impact funds is aligned with the market.**

The methodology used in the paper to investigate the risk-return of impact funds was dual, one methodology being applied for each hypothesis. The data used was time-series data on a defined dataset, also known as panel data or longitudinal data (Lefèvre, 2016; Wooldridge, 2015), based on a sample of 26 funds and of daily returns over the 2014-2018 period. On the one hand, to test for the first hypothesis, the working method relied upon economic and econometric models, by using the SPSS software. The different economic models used were Jensen's alpha (1968) and its generalization, as well as three multi-factor models, the Fama-French three-factor model (1992, 1993), Cararth four-factor model (1997) and Fama-French five-factor model (2015). The models enabled to compute the performance of the impact funds relative to the market by adding, in each model, different parameters for the risk level sensitivity. The econometric models were simple and multiple ordinary least squares linear regression, with the method enter. On the other hand, for the second hypothesis, the methodology was to compute the volatility through three statistical model, the standard deviation of returns, as well as the EWMA and the GARCH(1,1) variance. The differential in volatility from the impact funds and the markets could then be compared. The long-run trends could be analyzed through GARCH(1,1), also enabling an analysis of the evolution of the variance over time. For the risk analysis, all computations and graphs were performed in Excel through the creation of self-developed tools.

The results of the risk-return analysis of impact funds over the 2014-2018 period enabled to determine that, in overall, European open-end impact funds presented returns significantly in line with the market rate of return at a 1% confidence level while US open-end impact funds presented returns significantly different from the market at a 5% level, with an average Jensen's alpha of -1,29% computed with Fama-French 5-factor model at a 93,70% explanatory power. Overall, the risk of open-end impact funds tended to be higher than those of the market, both in the USA and in Europe, over the 2014-2018 period. The standard deviation, EWMA and GARCH(1,1) long-run volatility found higher volatilities for impact funds than for the market, except for the Netherlands and Belgium where one metric, the GARCH(1,1) long-term volatility, found an opposite conclusion at -3,32% and -0,41% respectively. The evolution of the GARCH(1,1) volatilities indicated impact funds volatilities to be higher than the market at frequencies higher than 70% for all the countries, except Belgium where the value dropped at 53,69%.

The difficulties and limits encountered, however, mitigate the results. Firstly, regarding the data, the absence of data on the impact of funds prevented to screen the sample for false "impact fund" denominations. Moreover, the backfill bias, survivorship bias, fund coverage across database and incompleteness of the data could not be excluded from the database. Secondly, for the sample, even though each fund himself encompassed several enterprises, the results were based on a small sample of 26 funds, due to many correlations and many impact funds created after 2014. The results, split by country, were thus not representative of the countries as some only had one fund, but rather of the region. Thirdly, for the performance analysis, the models encompassed many assumptions. Besides, most markets only had one outlier, yet 13 outliers had to be removed from the US data. Moreover, the explanatory power of the models, even though above 70% for half the analysis, was relatively low for Belgium (58,44%), Germany (46,69%) and Luxembourg (37,39%).

The paper is organized as follows. Section 2 investigates the impact investing funds and their industry. Section 3 exposes a literature review on the main studies and findings on the risk-return of impact funds, followed by Section 4 presenting a succinct literature review on the risk-return evaluation of mutual funds and open-end funds. Section 5 describes the data and methodology used in the analysis and Section 6 displays the results and conclusions of the analysis. Section 7 concludes.

2 A DEEPER VIEW ON IMPACT INVESTING FUNDS

The term *Impact Investing* or *Social Impact Investing* (SII) appeared in 2007 in Italy when it was coined by the Rockefeller Foundation (Donner & Huang, 2019). In the after-2008 crisis context, questions were raised about the financial markets and financial-result-only targeting investments (Chiappini, 2017; Shiller, 2013; Zingales, 2015). In the same period, as environmental awareness rose, the need for blended-value investment solutions soared and new sustainable finance solutions appeared worldwide (La Torre & Calderini, 2018).

Since 2007, the impact investing market has boomed. According to the Global Impact Investing Network (GIIN) annual survey (GIIN, 2019a) based on 208 impact investors, impact investing represented USD 239 billion assets under management (AUM) in 2018, with USD 514 billion invested since market inception. In 2018, impact funds represent 47% of investments realized. The market has been growing tremendously and will continue to do so in the upcoming years. Since 2014, impact investments grew at a 17% compounded annual growth rate (CAGR), with a 16% CAGR specific to the impact funds industry. On top of that, $200 million has been invested by the Rockefeller Foundation towards building a marketplace for impact investment (Shah, 2019). The GIIN has developed tools (Section 2.5, p.12) and widely used annuals reports on the market. Many for-profit institutions, as well as international organizations, also got involved in the field, including the OECD, the Organisation for Economic Co-operation and Development, by publishing reports on SII development as well as Prime Minister Cameroon who promoted the creation of the Social Impact Investment Taskforce, or SIIT, at the G8 in 2013 (Chiappini, 2017; Donner & Huang, 2019).

2.1 IMPACT INVESTING INDUSTRY AS A WHOLE

Among the definitions provided in the literature, impact investing is rooted between three major components: financial return; positive social and/or environmental impact; and the intention to generate such impact (Findlay & Moran, 2018; La Torre & Calderini, 2018). Chiappini (2017) insists on the need for the positive impact to be a declared intention rather than an accidental externality. Moreover, the favorable influence should be pursued *a priori* (Drexler & Noble, 2013).

The OECD (2015) identified seven key characteristics of social impact investment:

1. **The social target areas***:* The OECD, following on the Social Impact Investment Taskforce (Addis, Koenig, 2014) includes eight core target areas in the SII scope, being ageing, disability, health, children and families, public order and safety, housing, unemployment, and education and training (OECD, 2015, p.62). The OECD also allows for community, culture, arts, agriculture, environment and energy, water and sanitation, financial services (e.g. microfinance) and ICT (information and communication technologies) to be incorporated, provided that the investment is made on developed countries. Those areas are also considered as being part of impact investments by the GIIN (2019a).
2. **The beneficiary context***:* The beneficiaries are the "*population at-risk by social demographics, location or income*" (OECD, 2015, p. 64). The OECD definition brought more clarification on beneficiaries, previously considered by many as "*society as a whole*" (La Torre & Calderini, 2018, p. 18).
3. **The good/service**: Goods and services covered by impact investing are social goods/services, they are "*neither fully private nor fully public*" (OECD, 2015, p. 66). While the goods/services should have a positive impact on target-beneficiaries, the impact should be limited for non-beneficiaries under the profit-principle (OECD, 2015).
4. **The delivery organization***:* The social commitment of the delivery organization needs to be foremost and explicit, the intent alone is not enough. The organization should either "*engage in compulsory reporting, obtain external certification or label, or comply with legally binding constraints*" (OECD, 2015, p. 69).
5. **The measure of social impact***:* Social impact must be measured through formal evaluation, either qualitative or quantitative, with or without monetization (i.e. by computing the economic value generated, or not) (Brandstetter & Lehner, 2015; World Economic Forum, 2013). Further developed Section 2.5, p. 12.
6. **The investor intent***:* The social intent of the investor must be straightforward and demonstrated, similarly to those of the delivery organization. The investor needs to abide by "*compulsory reporting or legally binding constraints*" (OECD, 2015, p. 72).

7. **Return expectation***:* The return of SII is at least a payback of the principal invested, plus returns ranging from zero to market rate of return (MRR) of similar investments (Freireich & Fulton, 2009; Höchstädter & Scheck, 2015). Grants and profits above the MRR are thereby excluded from the sphere of SII. The SIIT, however, allows for returns above the MRR in the scope of SII (SIIT, 2014). Burckart (2015, p. 4) made a distinction between "*non-concessionary impact investment*" which yield the MRR and "*concessionary impact investment*" with return below the MRR, the lower return being a trade-off for the positive social and/or environmental impact. In 2018, out of 266 observations for the GIIN annual survey, 66% sought yields at the risk-adjusted market rate, 19% below the market yet closer to market rate and 15% closer to capital preservation. In the impact fund landscape, based on 169 respondents, 81% of funds managers were profit-seeking while 17% were non-profit seeking (GIIN, 2019a). Besides the traditional financial returns, Pay for Success (PFS) are another type of investment within the scope of SII where returns are linked to the social and/or environmental performance achieved (Donner, Huang, 2019).

Impact investing includes all sorts of traditional investments, including equities, bonds, loans and real assets (Rodin & Brandenburg, 2014), as well as more SII-specific asset classes, being social enterprises[1] and social impact bonds[2] (Donner & Huang, 2019). In 2018, largest investments identified by the GIIN annual survey 2019 were, out of 261 observations, in private debt (34% of capital invested) followed by public debt (16% of capital invested), private equity (14%), public equity (11%) and real assets (10%) (GIIN, 2019a).

The nature of impact investing itself is however still under discussion. It is considered either a new investment approach (World Economic Forum, 2013, p. 6), a new asset class, a new market or simply in the continuity of previous investment types (Chiappini, 2017).

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[1] Social enterprises are defined by the EMES Network as "*organizations with an explicit aim to benefit the community, initiated by a group of citizens and in which the material interest of capital investors is subject to limits*" (Defourny & Nyssens, 2006, p. 5).

[2] Social impact bonds SIB are also called *Pay for Success Bonds* or *Pay for Benefit Bonds*. SIB are instruments where financial returns are delivered once the social and/or environmental goals are achieved (Agrawal & Hockerts, 2019). Although named bonds, the instrument – generally issued by governments – rather consists of a "*contract for the delivery of social services*" (Clifford & Jung, 2016, p. 6).

Figure 1 - Spectrum of social and financial objectives. From Barnett, C., & Eager, R. (2017). New Frontiers for Evaluation in a Fast-Changing World. *Evaluation For 2030 Agenda*, p. 300.

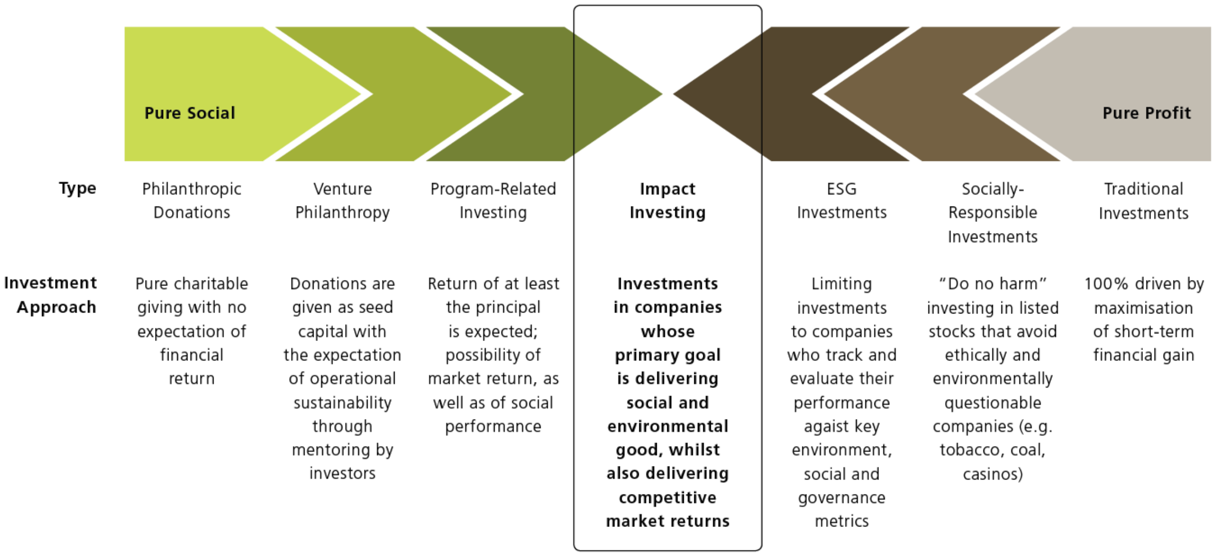
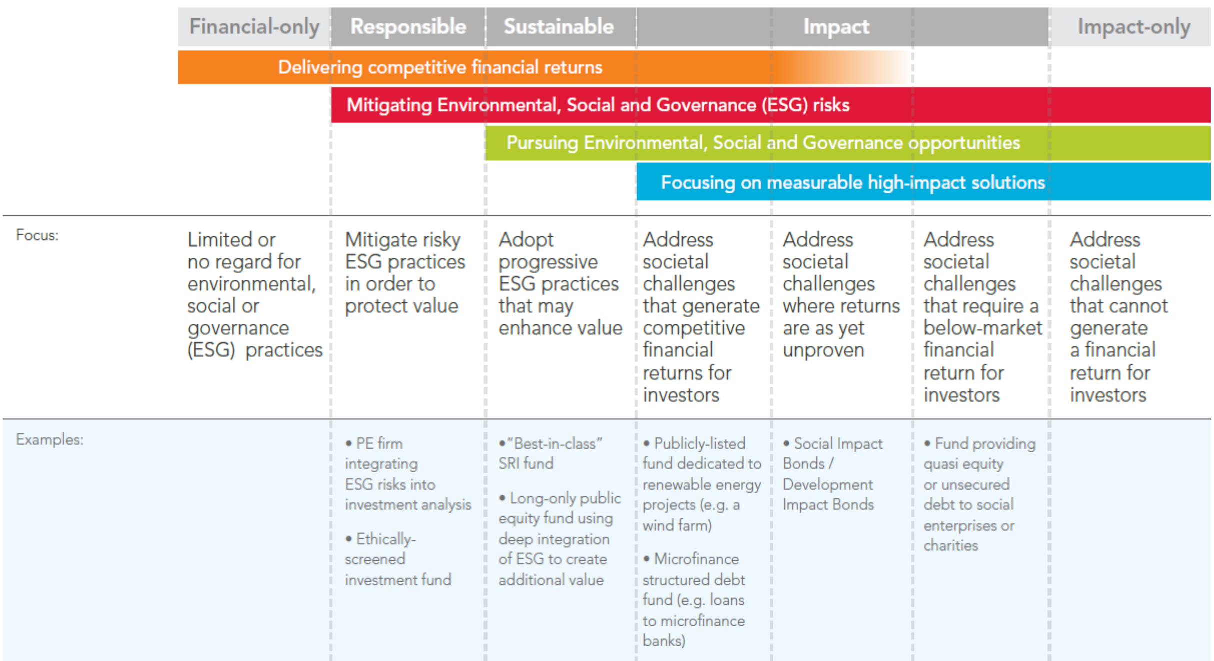


Figure 2 - Spectrum of Capital. From Bridges Investment Management. (2015). *The Bridges Spectrum of Capital: How we define the sustainable and impact investment market* [Online], p. 2. Retrieved May 7, 2019, from https://www.bridgesfundmanagement.com/wp-content/uploads/2017/08/Bridges-Spectrum-of-Capital-screen.pdf.



With its dual objective, impact investing is considered by many as a new investment paradigm (Bell, 2013; Chiappini, 2017; La Torre & Calderini, 2018). Impact investing combines traditional finance with the purpose of philanthropy (Höchstädter & Scheck, 2015). Impact investing encompasses a dual objective, one financial and one social/environmental. Hence, SII aims at the maximization of the *blended-value* of investments (Bugg-Levine & Emerson, 2011; Roundy *et al.*, 2017). This blended-value principle differentiates impact investing from traditional investment or philanthropy, where only one type of return is pursued, argues Weber (2016). To that extent, impact investing is often positioned on a continuum (Figures 1 and 2) between, on one side, traditional finance, and the other side, philanthropy (Barnett & Eager, 2017; Bridges Investment Management, 2015; Rodin & Brandenburg 2014; SIIT, 2014).

2.2 IMPACT FUNDS

Investment funds within the scope of impact investing are called impact funds or impact-oriented funds. They aim at generating both financial and measurable social and/or environmental impact. Main characteristics of impact-oriented funds are identified by Chiappini (2017):

1. **The mission** can be oriented towards social and/or environmental themes, outcomes and/or a specific risk-return.

2. **The strategy**, determined for the whole fund or at a more specific level, can either be focused on a specific country, investee, beneficiary, asset class, a certain investment diversification, a currency risk, a maturity of instruments, a specific investment mechanism (direct or indirect), an exit strategy, social and/or environmental measurements, and/or an investment process.

3. **The capital structure** of the fund can be divided into plain vanilla funds – where the profile of risk-return-impact is identical for each investor – or structured funds – where performance and risk vary among investors profiles. In a similar way to the securitization process, structured funds offer tranches based in risk-return-impact.

4. **The classification** of impact-oriented funds can be operated in different ways.

   A first classification can be established among three groups: commercial impact-oriented funds, typically the plain vanilla funds; non-commercial impact-oriented funds which focus primarily on impact; and quasi-commercial impact-oriented funds (Chiappini, 2017).

   A second classification is delivered by the Cabinet Office of the UK Government (2013): pari-passu (meaning "on equal footing") funds, risk-rewards funds and but-for funds. Pari-passu funds are typically the plain vanilla funds where risk-return-impact profiles are uniform. The main investors are foundations thereby building trust for other investors. Risk-rewards funds are funds where investors can choose their level of risk-return and where impact-seeking investors assume more risk and get more return. But-for funds are similar to risk-reward investors. The difference is that impact investors receive a smaller proportion of return as a trade-off for the impact created.

   A third classification is suggested by Chiappini (2017): Neoclassic are large environment-impact seeking funds investing in developed countries; futurist large social-impact seeking funds; hermetic are small environment-impact seeking funds investing in emerging countries; and illuminate are social-impact seeking funds investing in developed countries.

Impact investing through the means of funds is particularly sought for the investment qualifications and management skills of the general partner. Funds are valued by investors for their diversification and reduced transaction costs (GIIN, 2019a).

Characterized by their strategies, funds also enable direct access to certain themes, sectors or geographies. In 2018, out of 165 respondents from the GIIN annual survey, major strategy carried out by funds manager is a geographical focus (76%) with 43% targeting developed countries and 33% emerging countries (GIIN, 2019a). In parallel, funds differentiate from the instruments they invest in, 36% of the impact funds invest in private equity-only and 23% in private debt-only (GIIN, 2019a).

2.3 Market

Compared to the whole impact investing market, **impact funds industry** and other intermediaries represent on average (median) 47% of the number of investments realized in impact investments either directly or indirectly. According to the GIIN survey based on 165 observations, impact fund managers manage USD 87 billion, 33% of the overall impact investing assets under management (AUM) (GIIN, 2019a).

The market has been growing tremendously and will continue to do so in the upcoming years. In 2018, respondents indicated a capital raise of USD 14 billion while they plan to raise an additional USD 24 billion in 2019. The GIIN (2019a), based on 41 observation, identified a 16% CAGR in the impact funds industry AUM from 2014 to 2018, with the higher increase being for banks and diversified financial institutions (24% CAGR) and retail investors (21% CAGR).

According to the GIIN annual survey based on 165 fund managers, capital of impact funds are raised from diverse sources, mainly pension funds (17% of AUM), retail investors (16%), banks and diversified financial institutions (14%) and family offices and high net worth individuals (11%), foreign direct investments (8%), foundations (7%) and insurance (7%) (GIIN, 2019a).

Regarding the overall **impact investing market**, the GIIN annual survey reported USD 239 billion impact investing assets under management (AUM) in 2018, 10.9 billion more than in 2017 (GIIN, 2018; GIIN, 2019a). In total, 13,000 deals were carried out by respondents in 2018 amounting to USD 33 billion. In the same way, as the funds grew, the overall impact investing market soared in the last few years. Since inception in 2007, USD 514 billion of capital were invested by respondents through 196.019 investments. On a four-year time-lapse, 80 respondents that engaged in the previous GIIN studies grew their capital investment at a 17% CAGR. Current respondents plan a 13% growth in capital invested for 2019 (GIIN, 2019a).

Investments within the framework of SII are carried out across asset classes, sectors, and geographies (AlphaMundi 2010; Addis, McLeod & Raine, 2013). In 2018, out of the 259 observations of the GIIN annual survey, largest invested sectors in percent of AUM were energy (15% of AUM), microfinance (13%), financial services (excl. microfinance) (11%), food and agriculture (10%), water sanitation and hygiene (7%), housing (7%) and healthcare (6%) (GIIN, 2019a). On the geographical level, in 2017, 78% of respondents were based in developed countries. Half the capital they invested was deployed in emerging markets while the other half invested in developed markets. More specifically, in 2018, 28% AUM was invested in US and Canada, 14% in Latin America and the Caribbean, 14% in Sub-Saharan Africa, and 10% in Western, Northern and Southern Europe (GIIN, 2019a).

2.4 STAKEHOLDERS

The impact investing market encompasses three types of stakeholders, the demand-side, the supply-side and intermediaries. Impact funds act as intermediaries between the demand-side and capital providers (Clark, Emerson & Thornley, 2012).

Social goods, services providers, and demanders are labeled under the **demand-side** of impact investing (Chiappini, 2017). They are at the origin of the demand for funding. They are composed of "*community organizations, charities or non-profit organizations, social enterprises, social businesses, and social-driven businesses*" (OECD, 2015, p. 33), and encompass both for-profit and non-profit organizations (GIIN, 2019a).

The **supply-side** of impact investing is the capital providers. They are composed of "*foundations, high net worth individuals and philanthropists, banks and other financial services firms and intermediaries*" (OECD, 2015, p. 36). They consist of "*individuals, groups of investors or as institutional venture capital funds*" (Roundy *et al*., 2017, p. 3). Monitor Institute (Freireich, & Fulton, 2009, p. 31) distinguishes between "*Impact First investors*" and "*Financial First investors*" whether their primary goal is a positive impact or financial performance.

OECD's definition of **intermediaries** includes "*commercial banks, investment banks, independent financial advisors, dealers and exchanges*" (OECD, 2015, p. 39), inclusive of funds.

2.5 IMPACT MEASUREMENT

The GIIN (2019a), in its annual survey, identified that 98% of impact investors out of 208 respondents do either assess, evaluate or measure impact through various methods (GIIN, 2019a). Tools are rarely used one at a time but rather as a complementary one to another. While 66% carry out qualitative analysis, 63% exploit proprietary metrics and frameworks, 49% use metrics aligned with IRIS and 37% make use of frameworks and assessments (GIIN, 2019a).

O'Flynn and Barnett (2017) classify impact measurement into four categories: (1) Monetization approaches; (2) Scorecards, indicators, and ratings; (3) Statistical tools and counterfactuals; and (4) Qualitative tools.

Firstly, the **Monetization approach** consists of attributing a pecuniary value to the social and/or environmental value created (O'Flynn & Barnett, 2017). The Social Return on Investment (SROI) is a ratio indicating the present value of the impact generated in percent of the money invested. The Cost-effectiveness analysis (CEA) and the Cost-benefit analysis (CBA) consist of assessing and comparing the monetized value of impact on the costs to produce impact (Chiappini, 2017).

Secondly, the **Scorecards, indicators, and ratings** are composed among others of the Impact Reporting and Investment Standards (IRIS) catalog, the Global Impact Investing Rating System (GIIRS), the B-Corp Certification and the Environmental, social and governance (ESG) toolkit (O'Flynn & Barnett, 2017). The IRIS Catalogue, part of the IRIS+ created by the GIIN, lists the metrics which are classified according to the enterprise and sector's characteristics (GIIN, 2019b). The GIIRS set up by B-Lab and the B-Corp Certification both offer ratings based on the impact model of the company assessed (Donner & Huang, 2019). The Global Reporting Initiative (GRI) Standards and the Sustainability Accounting Standards Board (SASB) offer reporting standards on the sustainability and financial impact of the firm (GRI, n.d.; SASB, n.d.).

Thirdly, the **Statistical tools, experimental and quasi-experimental methodologies** are key analytical tools to compare the impact and assess its creation. Two situations are compared, one being without impact implementation and the second while trying to create impact. Experimental methods are also used to determine causal links (O'Flynn & Barnett, 2017).

Finally, **Qualitative tools** are typically used along with other measurement tools. They consist of more ancillary evaluation methods. Example of qualitative tools includes Qualitative impact protocol (QUIP), Success measures and Social rating (O'Flynn & Barnett, 2017).

Conclusion

While the industry is still new, the market and the use of impact funds are growing tremendously. The characteristics of impact funds, their industry, stakeholders and measurement tools, although still needing clarifications in the baselines from practitioners, enabled to specify the concepts. Their risk and returns could thereafter be reviewed.

3 RISK-RETURN OF IMPACT FUNDS, A LITERATURE REVIEW

3.1 FINANCIAL PERFORMANCE OF IMPACT FUNDS

According to academics and practitioners, returns expectations of impact investing instruments must range from capital preservation to the market adjusted rate of return (MRR) (Freireich & Fulton, 2009; Höchstädter & Scheck, 2015; OECD 2015). Seeking returns above the MRR is thus excluded from the scope of SII because an outperformance objective would imply preferring the financial purpose over the impact goal. The investors would drift away from their impact purpose while impact investments rather aim at the maximization of the blended value.

In the GIIN annual survey, in 2018, 84% of for-profits impact funds yielded returns equal to market rate, compared to 28% of non-for-profits impact funds. The remaining of funds performed returns below market rate (GIIN, 2019a).

The financial performance of impact funds was not been extensively studied in the literature. Impact investing returns were rather researched on the three major instruments invested: private equity, private debt and real assets (GIIN, 2017b).

Regarding **private equity** impact investments, Bouri, *et al*. (2015) and Gray, *et al*. (2015) in their studies found out that that the MRR can be reached. Returns, however, varies with the investments, even those who target the MRR. Bouri, *et al*. (2015) also pointed out the great difference between investors' expectations and actual returns. Their study determines that small and emerging market impact investments outperformed and highlighted the importance of good manager selection (GIIN, 2017b).

Focusing on **private debt** impact investments, the studies carried out by Symbiotics (2017) and Castellas, Findlay, and Addis (2016) showed that returns of private debt tend to be comparable to expectations. EngagedX-Social Investment Research Council (2015) and Brown, Behrens, and Schuster (2015) found out that even the high-risk investees could almost reach capital preservation (GIIN, 2017b).

Regarding **real assets** impact investments, Castellas, *et al*. (2016) and Dithrich, *et al*. (2017) report the volatility of returns as it is the case for real assets outside the scope of SII. Dithrich, *et al*. (2017) also indicated outperformance among small real assets impact investments.

3.2 Risk of impact funds

The impact funds, just like any financial markets, are confronted with a vast array of risks. Barby and Gan (2014), and Chappini (2017) list some of the most significant risks, while the GIIN annual survey provides information on the hazard sentiment of impact investors.

Barby and Gan (2014) identify five risks faced by impact investors:

1. **The capital risk** is the risk associated with the loss of the principal invested;
2. **The exit risk** is for illiquid or non-transferrable instruments, as instruments invested by impact funds are often illiquid;
3. **The unquantifiable risk** is linked to unpredictable events;
4. **The transaction cost risk** is related to due diligence, structuring, and monitoring;
5. And **the impact risk** is those of negative impacts on stakeholders.

Besides, Chappini (2017) expands the list of risks by mentioning:

6. **The concentration risk** is a hazard faced when diversification is reduced and depends on the strategy and the focus of the fund;
7. **The social risk**, more specific to impact funds, is "*the possibility that the achieved social or environmental impact is lower than expectation due to unpredictable events that involve delivery organizations' activity or the life of end beneficiaries*" (Chiappini, 2017, p. 74);
8. Other risks that can be faced are some **reputational risk, credit risk, market risk, interest rate risk, country and currency risk**, and **operational risk**.

The GIIN annual survey (2019a) identified the risks regarded as the most significant by impact investors. Business model and execution management risks are considered the most severe, followed by country and currency risk, liquidity and exit risk, macroeconomic risk and financing risk. In 2018, based on 266 observations, significant risk events were faced by 22% of impact investors. Such events include poor governance, extreme weather events, political trouble, currency devaluation and trade relation with the USA (GIIN, 2019a).

Conclusion

Explained by the recent sector, the risk and returns of impact funds were barely studied in the literature, especially form a quantitative point of view. Researches of open-end impact funds were rather limited to the mutual funds outside the scope of impact investing.

4 RISK-RETURN OF OPEN-END FUNDS, A LITERATURE REVIEW

4.1 EVALUATION OF THE FINANCIAL PERFORMANCE OF FUNDS

This section offers a literature review of the results of mutual funds' performance studies and of the measures developed to assess the financial returns of funds. Researches on mutual funds' performance have been carried out to determine whether mutual funds add value and lead to "abnormal performance" relative to the risk-adjusted market portfolio. The hypothesis tested consisted of knowing whether funds manager, with their expertise and with the use of private information, could lead to financial performance above the MRR (Nitzsche, Cuthbertson & O'Sullivan, 2006).

The starting point of the **mutual funds' performance analysis** comes with Jensen (1968), Sharpe (1966) and Treynor (1965). Their results indicated no abnormal returns, thus supporting the Efficient Market Hypothesis (EMH).

Thirty years later, Ippolito (1989) came to the opposite conclusion and provides evidence of the existence of inefficiencies on the market. Many authors study the persistence of performance and highlighted the evidence of repeated winners and losers among funds (Grinblatt & Titman, 1992; Goetzmann & Ibbotson, 1994; Volkman & Wohar; 1996). Elton, Gruber, Das, and Hlavka (1993) proved that the inefficiencies, captured by mutual funds, fail to cover the expenses induced by the management of the fund. Malkiel (1995) came to the same conclusion regarding gross returns of funds, as only a few funds managers achieved statistically significant outperformance.

In the following researches, Elton, Gruber, Das, and Hlavka (1993), and Malkiel (1995), along with Carhart (1997) also include the survivorship bias (further developed Section 5.1, p.21) in the performance analysis and benchmark errors which, once included, enables them to refute the outperformance results. Survivorship bias, further studied by Elton, Gruber, and Blake (1996a) and Grinblatt, and Titman (1994), confirmed to induced biases results by artificially increasing the returns.

Expenses and turnovers effects lead to various conclusions among studies. Although expenses were associated with the performance by Sharpe (1966), Golec (1996) found them related to poor returns. Hooks (1996) and Dellva and Olson (1998) find positive or negative effects of loans on performance respectively. Concerning the effect of expenses on the turnover of the returns of the funds, authors are again split among those who find turnover increases (Friend, Blume & Crockett, 1970; Grinblatt & Titman, 1994; Wermers, 2000); or decreases (Carhart, 1997; Malkiel, 1995).

The authors, for their analysis, conceived the standard **measures of performance**. Sharpe (1966) created the Sharpe ratio, based on the assumption of a risk-free rate. Treynor (1965) ratio is very similar to the one of Sharpe except that is measure risk relative to market using beta as a proxy for risk. Jensen's alpha (1968) based on the Capital Asset Pricing Model (CAPM), the alpha measuring the excess return of the portfolio compared to the adjusted risk of the market.

Goetzmann et al. (2007) in their study show that Sharpe, Treynor and Jensen's single parameter measures, although widely used, are biased by a dynamic leveraging of a portfolio. Such leveraging, through a linear effect on returns and nonlinear effect on the standard deviation, enables to manipulate the ratios by for example decreasing the standard deviation and increasing the Sharpe ratio. Single index models lead to the appearance of more sophisticated models based on multi-index benchmarks (Elton & Gruber, 2013).

Elton, Gruber, and Blake (1996b) analyze performance using multi-factor models. Based on the market returns, a size factor, growth vs. value factor and bond index factor, both analyses reach the same conclusion of the absence of outperformance.

Among acknowledged multi-factor models, Fama and French (1992, 1993) expanded the Capital Asset Pricing Model with two additional variables, the return on small stocks minus those of large stocks and the return of high book-to-market stocks minus those of low book-to-market stocks. Jegadeesh and Titman (1993) demonstrated the existence of the momentum effect on stocks, that is the difference in returns of portfolios with the highest and lowest performing securities. Following their finding, Cararth (1997) completed the Fama-French model with the momentum factor. Fama and French (2015) later appended two bond factors to the model. Adding bond factors enables to cover for the incorporation of long-term bonds in mutual funds (Elton, Gruber, and Blake, 1996a, 1996b).

With the emergence of multi-indexed models, Jensen's alpha remains a key indicator. The same measure of alpha was generalized and applied to the multi-factor models to assess the performance more accurately, being the difference between risk-adjusted predictions and realized returns (Elton & Gruber, 2013).

4.2 Evaluation of the risks of funds

Early through the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) and the Arbitrage Pricing Theory of Ross (1976), and further demonstrated by French, Schwert, and Stambaugh (1987), risks of securities are positively linked to their returns.

The basic measures of risk in traditional finance lie in the standard deviation of the return (Simons, 1998). The metric, although quite simple, is included in many models of expected returns. Derived from the standard deviation of returns, the tracking error measures the standard deviation of the excess return relative to the risk-free rate (Simons, 1998). As an alternative risk measure, the downside risk is aimed at measuring the variability of losses rather than the variability of both gains and losses. The intention was to assess the risks on an investor perspective. However, the downside risk is highly correlated to the standard deviation, providing only a few now information (Simons, 1998).

The Value at Risk (VaR) developed by the Group of Thirty (1993) measures the maximum potential loss on a portfolio in the best scenarios at a 99% confidence level on a day. The VaR is the basis point for the risk analysis of financial institution under Basel and Solvency regulations (De Wynendaele, 2016).

Shifting away from one-factor models of volatility, multi-factor intertemporal models of volatility have been developed. Engle and Lee (1999) demonstrated the aggregate volatility to be affected by shocks over time. They conclude that two-factors models of volatility provide more accurate estimates than one-model factors, conclusions which further researches agreed on (Alizadeh, Brandt, & Diebold, 2002; Bollerslev & Zhou, 2002; Chacko & Viceira, 2003; Chernov *et al*., 2003; Engle and Rosenberg, 2000).

Engle (1982) developed the ARCH(p) (Autoregressive Conditional Heteroscedasticity) model. ARCH consider a conditional variance, a function of past squared errors (Van Wynendaele, 2017). Bollerslev (1986) and Taylor (1986) generalized the ARCH model by creating the GARCH (Generalized ARCH), enabling a more flexible lag structure (Lee, Chen, & Rui, 2001). The two models enable to capture the clustering of volatility over time as well as the non-normality of residuals distributions (Mala & Reddy, 2007). Derived from the GARCH, the EWMA (Exponentially Weighted Moving Average) was later introduced by JP Morgan & Reuters (1996). The EGARCH (Exponential GARCH) was proposed by Nelson (1991) as an alternative to the GARCH model limitations.

To deal with the strict statistical assumptions and the amount of market data required linked with time-series models, ANN (Artificial Neural Network) was presented as an alternative model (Roh, 2007). ANN "*is a nonparametric method and can forecast future results by learning the pattern of market variables without any strict theoretical assumption*" (Roh, 2007, p. 916).

CONCLUSION

Compared to the impact funds industry, the literature on the risks and returns of mutual funds, in general, was broader and more ancient. While the debate on the performance of mutual funds is still active among academics, the risks are mostly analyzed through a standard measure. Other models, however, enable to complement the risk analysis.

5 DATA AND METHODOLOGY

5.1 IMPACT FUNDS DATA

The data used in the thesis is longitudinal data, also called panel data (Lefèvre, 2016; Wooldridge, 2015). A panel of open-end impact funds was selected, which for time-series data was retrieved for a defined period. The funds selected in this thesis fulfilled the following criteria: impact open-end funds; investing in equities; domiciled in Europe and the United-States; created before 2014; and whose historical net asset values (NAV) were available. The database exploited to retrieve the funds was Bloomberg, using the SEC security finding function with the "impact" keyword.

The dataset lied upon a strong assumption: funds including the "impact" keyword – thus calling themselves "impact funds" – were considered as impact funds, irrespective of any possibilities of false denominations. Chiappini (2017), however, studied the compliance of so-called impact funds with the impact investing characteristics defined by the OECD and showed that, in practice, these funds rarely met the conditions. For this thesis, this strong assumption was taken because of missing data and because of the lack of homogeneously used measuring tools and certifications. There was indeed no direct access to information enabling to assess and compare the impact funds on the industry. Consequently, the shortage of uniformity prevented to have a screening of funds that would have been consistent among all funds and therefore statistically representative.

Historical data was retrieved for a panel of funds for the 2014-2018 period. The data used for the analysis was quoted in Euro and US dollars depending on the domicile of the funds. The daily log-returns of the funds were computed using the following formula:

$$R_t = \ln\left(\frac{NAV_t + DIST_t}{NAV_{t-1}}\right) \tag{5.1}$$

Where NAV_t is the closing net asset value and $DIST_t$ is income and capital gains distributions (Simons, 1998).

The sample of data included 26 funds (detailed list Annex 1, p. 54), among which 10 were domiciled in the US and 16 in Europe, more specifically in the Netherlands (1), Belgium (1), France (1), Germany (1) and Luxembourg (12). They either had an international focus (15 funds) or a regional fund on the US (7 funds) or Europe (4 funds). The funds were quoted in USD (11 funds), EUR (10 funds), GBP (3 funds), HUF (1 fund) and CZK (1 fund). Funds had inception dates ranging from June 1991 to November 2013 with a median in August 2008. Half the funds had management institutions that are GIIN members while only a few (6 funds) were listed on the ImpactBase database.

The dataset of open-end funds created and used in this thesis, although trying to be as much representative as possible, included a set of biases and problems such as listed by Elton and Gruber (2013): a backfill bias, incomplete data for small funds, a difference of fund coverage across databases and a survivorship bias.

1. **The backfill bias** is linked to incubator-fund. These funds are set up in droves with limited capital and then only those successful are publicly launched (Elton & Gruber, 2013). The datasets are then biased because they only include the publicly opened incubator-fund, those who performed well, creating an upward bias. Besides, their returns before public launching are recorded in the database.

2. **The incompleteness of the data for small funds** comes from the absence of obligation for small funds to disclose their performance (Elton & Gruber, 2013). These funds are less recorded or not at all. Only well-performing funds end-up being recorded in the standard databases (Elton, Gruber & Blake, 2001).

3. **The fund coverage across databases is different**. Depending on the database, some funds can be included or not, leading to different datasets thus divergent conclusions for the same analysis (Elton & Gruber, 2013).

4. **The survivorship bias**, as widely studied in the funds' performance literature (Section 4.1, p.16), is the problem that funds' databases often include the funds that are still active at a certain point of time (Elton & Gruber, 2013). The day the dataset is retrieved, only the funds who survived are present in the database, thus ignoring the performance of all funds who existed before and did not survive. This upward bias was found by Elton, Gruber, and Blake (1996) to increase the alphas by 35 basis point to 1%.

5.2 MARKETS AND BENCHMARKS

The markets instigated in the thesis each encompass a market benchmark and a risk-free rate benchmark (Table 1). The **markets** were the domicile countries of the impact funds sample. The returns of the individual funds were aggregated into equally weighted "portfolios" according to these markets. The funds in the sample were tested for their correlations, whereas those with correlations higher than 0.99 were excluded. Although a market-capitalization-weighted "portfolio" would have seemed more consistent with the actual characteristics of the markets, such a ponderation would not have been representative of the total impact funds industry returns as the net asset values (NAV) of the funds of the sample varied widely across the sample (Annex 1, p.54). The results of a NAV-weighted analysis would indeed have been influenced by the largest market cap, thus ignoring small-cap funds.

The **market benchmark** was aimed at replicating the market portfolio of all tradeable assets, as stated in the Capital Asset Pricing Model (Cuthbertson, Nitzsche & O'Sullivan, 2010). The market indexes selected were the S&P 500, the AEX index, the BEL20 index, the CAC40 index, the DAX index, and the LUXXX index. These market portfolios were those set by Bloomberg as benchmarks for the funds of the sample.

The **risk-free rates of return** used in the analysis were the Overnight Indexed Spread (OIS) rates, namely the Fed Funds rates for the US, and the Euro Overnight Index Average (EONIA) rates for Europe. The OIS rates although less used than the London Inter-bank Offered Rate (LIBOR), were claimed to be a better proxy for the actual risk-free rate (Hull, 2014; Hull & white, 2013). Data was retrieved from Bloomberg in US dollars for the Fed Funds rates and in Euro for the EONIA. Annual rates were translated to daily rates.

Table 1: Summary of the markets and the respective benchmarks

Region	Market	Market benchmark	Risk-free rate benchmark
USA	USA	S&P 500	Fed Funds rates
Europe	The Netherlands	AEX Index	EONIA rates
	Belgium	BEL20 Index	
	France	CAC40 Index	
	Germany	DAX Index	
	Luxembourg	LUXXX Index	

5.3 FINANCIAL PERFORMANCE EVALUATION METHODOLOGY

The performance analysis was aimed at testing hypothesis 1 of the thesis. The analysis was based on both economic and econometric models and was performed using SPSS. The economic models included the Jensen's alpha (1968) generalized and further applied to three multi-factor models, the Fama-French three-factor model (1992, 1993), Cararth four-factor model (1997) and Fama-French five-factor model (2015). Jensen's alpha is used as an indicator of the performance of funds, by testing for its significance. The econometric models are simple and multiple ordinary least squares linear regression, with the method enter. The statistical tool, used to perform the regressions and the statistical tests, is the SPSS software.

On the one hand, the first **economic model** is the Jensen's alpha. Jensen's alpha was developed by Jensen (1968) based on the CAPM of Sharpe (1964) and Lintner (1965). Jensen's alpha measures the excess performance relative to market risks.

$$R_{pt} - R_{ft} = \alpha_t + \beta_p\left(R_{Mt} - R_{ft}\right) + \varepsilon_{pt} \qquad (5.2)$$

Where α_t is Jensen's alpha, that is the excess return of the portfolio after adjusting for the market, R_{pt} is the return on portfolio p, R_{tf} is the risk-free rate of return, R_{Mt} is the return on the mean-variance efficient portfolio, β_p is the sensitivity of the excess return on the portfolio p to the excess return on the market, ε_{pt} is the excess return of portfolio p not explained by the other terms in the equation and t is the time of occurrence (Elton & Gruber, 2013).

The three following models used for the thesis are multi-factor models. Based on these, the generalization of Jensen's alpha enables to assess the performance. The generalization of Jensen's alpha is the difference between risk-adjusted predictions and realized returns.

$$R_{pt} - R_{ft} = \alpha_t + \sum_{k=1}^{K} \beta_{pk} I_{kt} + \varepsilon_{pt} \qquad (5.3)$$

Where I_{kt} represents any influences on returns and β_{pk} represents sensitivities to these influences (Elton & Gruber, 2013).

In this thesis, the alpha is used as a measure of the difference between the predicted returns, based on risk levels and the market, and the realized returns. A significant zero alpha, therefore, indicates that the performance is aligned with the market.

The generalization of Jensen's alpha is applied to the multi-factor models. The first multi-factor model is developed by Fama and French (1992, 1993) as an extension of the CAPM by adding two additional risk-factors, the "size" variable, noted SMB_t (small-minus-big) and the "book-to-market" factor, noted HML_t (high-minus-low). The two factors enable to capture systematic economic risks (Cuthbertson, Nitzsche & O'Sullivan, 2010).

$$R_{pt} - R_{ft} = \alpha_{pt} + \beta_{p1}(R_{Mt} - R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \varepsilon_{pt} \quad (5.4)$$

The second model used, elaborated by Cararth (1997), increments the Fama-French three-factor model with the "momentum" factor MOM_t (highest-minus-lowest performing firms) (Cuthbertson, Nitzsche & O'Sullivan, 2010).

$$R_{pt} - R_{ft} = \alpha_{pt} + \beta_{p1}(R_{Mt} - R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \beta_{p4}MOM_t + \varepsilon_{pt} \quad (5.5)$$

Fama and French (2015) extend their three-factor model into a five-factor model with a "profitability" factor, noted RMW_t (robust-minus-weak) and "investment style", noted CMA_t (conservative-minus-aggressive).

$$R_{pt} - R_{ft} = \alpha_{pt} + \beta_{p1}(R_{Mt} - R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \beta_{p4}RMW_t + \beta_{p5}CMA_t + \varepsilon_{pt} \quad (5.6)$$

On the other hand, the **econometric model** employed on these economic models is a multiple linear ordinary least squares regression (OLS), using the method enter[1]. The models, therefore, rely upon the hypothesis of the multiple OLS. A model validity screening enabled to test for the goodness of fit of the model and the assumptions. The goodness of fit was analyzed with the adjusted R squared, and for outliers in the observations.

The assumptions of the multiple linear regression (MLR) are called the Gauss-Markov assumptions: (MLR.1) the linearity in parameters, (MLR.2) the random sample, (MLR.3) a zero conditional mean, (MLR.4) the absence of collinearity, (MLR.5) the homoscedasticity of the error. Under these assumptions, the estimators of the parameters are called B.L.U.E. Best

[1] The method enter is "*a procedure for variable selection in which all variables in a block are entered in a single step*" (IBM, n.d.). "*Method selection allows you to specify how independent variables are entered into the analysis. Using different methods, you can construct a variety of regression models from the same set of variables*" (IBM, n.d.).

Linear Unbiased Estimators and are unbiased estimators with the minimum variance of the parameters, according to the Gauss-Markov theorem. A supplemental hypothesis is (MLR.6) the normality of the error (Lefèvre, 2016; Wooldridge, 2015). Nonlinearity, homoscedasticity, and normality of residuals are tested in this thesis by using scatterplots and P-P plots (Annex 2, p. 55) while multicollinearity is tested using the VIF factor[1] (Lefèvre, 2016).

The methodology used in the thesis to assess performance lie on a set of concepts and assumptions. First, the concept of abnormal performance is linked to mispriced securities and market efficiency. Markets are assumed by most investors to be efficient when pricing securities. The models presented are based on the Efficient Market Hypothesis. Yet, the generalized alpha is based on inefficiencies which could enable fund managers to capture abnormal returns (Cuthbertson, Nitzsche & O'Sullivan, 2010).

Secondly, the benchmark applied in theory for Jensen's alpha computations is the conditional mean-variance efficient portfolio (Cuthbertson, Nitzsche & O'Sullivan, 2010). In practice, the benchmarks used in the thesis are proxies for the market portfolio of all tradeable assets, as stated in the Capital Asset Pricing Model. Mean-variance efficient portfolios are indeed impossible to establish with more than 20 assets as well as is the weight attached to these assets (Britten-Jones, 1999). As a result of that choice, non-zero alphas indicators of performance are then inevitably biased and cannot estimate abnormal performance rigorously. Results rather indicate that the tested portfolio, when added to the market benchmark, improve the proxy of the conditional mean-variance efficient portfolio (Cuthbertson, Nitzsche & O'Sullivan, 2010).

Thirdly, the additional factors being SMB, HML, MOM, RMW, and CMA are factors mimicking the portfolio analyzed. In practice, due to a large number of funds themselves constituting the portfolio, the daily values of the factors are retrieved directly from French website (2019), both for the European and for the US market. These values are proxies of the American and European markets respectively.

[1] Absence of multicollinearity assumed when VIF < 10.

5.4 VOLATILITY EVALUATION METHODOLOGY

To test for hypothesis 2, the volatility of the impact funds sample is estimated using three metrics: the standard deviation, the EWMA, and the GARCH(1,1) model. The three models are the most commonly used and can be qualified as linear squared deviation (LSD) estimators and as historical volatility measures (Ederington & Guan, 2005). All computations and graphs were performed in Excel through the creation of self-developed tools.

The standard deviation of returns is a non-conditional metric of the realized volatility of the returns over a certain period. The standard deviation can be estimated with the formula:

$$\sigma^2 = \frac{1}{T+1}\sum_{i=1}^{T}(R_t - \bar{R})^2 \tag{5.7}$$

Where $T + 1$ is the number of observations, R_t is the log- return at time t (Formula 5.1, p.20) and $\bar{R}$ is the average return over the period (Hull, 2014; Simons, 1998).

The standard deviation, although widely used, encompasses certain limitations. The residuals the model are assumed to have a homoscedastic distribution, meaning that the variance of the errors is constant (Brooks, 2014). Time series, however, are not standardized models and the variance of their error is not always constant. Moreover, the standard approach does not consider the variance clustering effect. This effect relates to the tendency of the variance to cluster in time, the large changes in prices being more probable when large changes in prices occurred in the directly previous period (Brooks, 2014). Besides, when estimating present volatility, the standard deviation fails to measure the current level of risk.

As an alternative derived from the standard deviation, the EWMA aims at better evaluating the current level of risks. The particularity of EWMA comes from the weighted affected to the observations. While the standard approach considers returns irrespective to when they occurred, the EWMA attributes largest weighted to the most recent observations, the weight then declines exponentially as the observations become more ancient (Brooks, 2014). Most recent events are indeed more likely to affect present volatility. This effect is captured by the EWMA, which can be stated as:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)u_{t-1}^2 \tag{5.8}$$

Where σ_t^2 is the EWMA variance at time t, λ is the smoothing parameter, also called persistence parameter and u_{t-1}^2 is the squared log-return of the previous period. By developing the formula and replacing σ_{t-1}^2 by the equation (5.8) for the previous period, the equation (5.8) can be written as:

$$\sigma_t^2 = (1-\lambda)\sum_{i=1}^{T} \lambda^{t-1} u_{t-i}^2 + \lambda^T \sigma_{t-T}^2 \tag{5.9}$$

For a large T, as it is the case in this thesis, the $\lambda^T \sigma_{t-T}^2$ parameter becomes insignificant and can be removed, turning the EWMA variance estimation into a sum of weighted squared returns, with a weight equal to $(1-\lambda)\lambda^{t-1}$ (Hull, 2014).

In this thesis, as the timespan T was large, the $\lambda^T \sigma_{t-T}^2$ parameter was ignored. Moreover, the persistence parameter λ was set at 94%, as fixed by J.P. Morgan in its database RiskMetrics. The 94% λ level was found to be the best at estimating the anticipated variance (Hull, 2014).

The GARCH, used in the thesis, enables to compute the variance each day as well as a long-run variance, that is constant over time. GARCH is the generalization of the ARCH model from Bollerslev (1986) and Taylor (1986). The ARCH model, developed by Engle (1982), allows for the variance to vary over time by introducing a conditional variance depending on the previous values of the squared error. The GARCH model enables to tackle the lags count[1] by including all previous variances in the model using only three parameters. Besides, the GARCH model enables to reduce the number of non-negativity constraints on parameters by reducing the number of parameters (Brooks, 2014). The GARCH (1,1) model formula can be expressed as:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5.10}$$

$$\sigma_t^2 = \gamma V_L + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5.11}$$

Where σ_t^2 is the conditional variance, u_{t-1}^2 is the squared observation of the past period and σ_{t-1}^2 is the conditional variance of the previous period. The conditional variance is the function of a long-term average fixed-parameter ω, the volatility of the past period αu_{t-1}^2 (under the

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[1] The ARCH model includes the variance of previous periods in its computation. In ARCH(q), the lag counts *q* are the number of previous variances included in the formula. One main issue in ARCH(q), that is overcome by GARCH, was to determine the value of *q* (Brooks, 2014).

zero-mean of residuals assumption) and the variance during the past period. The variance during the previous period is itself a function of the past period volatility and variance, allowing for the conditional variance to be a function of all previous periods volatilities and variances (Brooks, 2014).

In the GARCH model, the unconditional variance of the residuals (V_L) is set as constant and computed using the following formula:

$$V_L = var(u_t) = \frac{\omega}{1-(\alpha+\beta)} \tag{5.12}$$

Provided that $\alpha + \beta < 1$. If $\alpha + \beta \geq 1$, u_t is not defined, this is known as "non-stationarity in variance" (Brooks, 2014).

In the thesis, the GARCH long-run variance (V_L) provided information on the long-run tendency of the risks. From the long-term variance, the volatilities could be computed for each period, enabling graphic comparisons of their evolution compared to the market.

The parameters estimation is made possible by using the Solver function in Excel and through the maximum likelihood method. This method searches for the best possible fits for the values of the parameters of the model by maximizing a likelihood function (Brooks, 2014). As the function is a multiplicative of the historical data, its logarithm was taken to turn it into an additive function, therefore enabling to maximize it. The likelihood function optimized in this thesis is the function presented by J. Hull (2014):

$$\sum_{t=1}^{T}\left[-\ln(\sigma_t^2) - \frac{u_i^2}{\sigma_t^2}\right] \tag{5.13}$$

Conclusion

Using longitudinal data, and through a dual methodology, the risk and return analysis is based on economic, econometric and statistical models: the Jensen's alpha (1968), the Fama-French three-factor model (1992, 1993), the Cararth four-factor model (1997), the Fama-French five-factor model (2015), the simple and multiple Ordinary Least Squares linear regression, the standard deviation of returns, the EWMA, and the GARCH(1,1) variance.

6 RESULTS

6.1 RETURN ANALYSIS EMPIRICAL RESULTS

The performance analysis investigated the performance of open-end impact funds relative to market performance. The assessment was based on the generalization of Jensen's alpha as an indicator of alignment with the market, by testing for its significance (Section 5.3, p.23).

For the **US open-end impact funds**, relative to the S&P 500 market benchmark over the 2014-2018 timespan (Table 2), a zero-alpha was rejected at a 5% confidence level for each of the models tested. The average values of alpha for each of the four models were of -1,3%, more precisely, -1,34% for the CAPM, -1,27% for Fama-French 3-factor (3F) and Cararth and -1,29% for Fama-French 5-factor (5F).

Regarding the goodness of fit, the regression was based on 10 American open-end impact funds and 1277 observations. The four models presented adjusted R squared of 0,92 and 0,94. Largest adjusted R squared was observable for the Fama-French 5F model. With five factors, the model brought the largest explanatory power compared to the others. The results were obtained after screening for outliers, by removing 13 extreme values, to B.L.U.E. estimators of the models and to comply with the multiple OLS regression assumptions (Section 5.3, p. 23). After screening, assumptions of linearity, homoscedasticity, and normality of residuals were verified in the linear regression (Annex 2, p.56).

Table 2: OLS regression on US funds with S&P index

	CAPM		**Fama-French 3-Factor**		**Cararth 4-Factor**		**Fama-French 5-Factor**	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	-0,013**	0,025	-0,013**	0,021	-0,013**	0,021	-0,013**	0,019
β (Rm-Rf)	0,932***	0,000	0,928***	0,000	0,928***	0,000	0,918***	0,000
β SMB			0,166***	0,000	0,162***	0,000	0,161***	0,000
β HML			0,033***	0,002	0,022*	0,064	0,032**	0,027
β MOM					-0,018**	0,032		
β RMW							-0,032*	0,068
β CMA							-0,041*	0,071
Adj. R^2	92,41%		93,58%		93,60%		93,70%	
N	1277							
Outliers removed	13							
Sample of funds	10							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

For the **European open-end impact funds**, the computations were realized relative to five markets and their benchmarks, the Netherlands with the AEX, Belgium and the BEL20, France and the CAC40, Germany and the DAX, and Luxembourg and the LUXXX index.

On the one hand, for the impact funds in **the Netherlands**, relative to the AEX index (Table 3), one generalization of Jensen's alpha was significant at a 5% level, in the CAPM, at an average value of 2,40%. For the three other models, alphas were significantly different from zero at a 10% confidence level, with average values of 2,1% in Cararth model and of 2,2% in Fama-French 3F and 5F.

Regarding the goodness of fit, the models evaluated one Dutch open-end impact fund, on 1289 daily returns. The models all presented adjusted R squared of 71%. Again, Fama-French 5F provided the best-adjusted R squared, at 71,27%. The OLS was screened for outliers. Three extreme values were removed from the data sample to comply with the OLS assumption. After checking for the assumptions, all hypothesis were graphically verified (Annex 2, p.57).

Table 3: OLS regression on Dutch funds with AEX index

	CAPM		**Fama-French 3-Factor**		**Cararth 4-Factor**		**Fama-French 5-Factor**	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	0,024**	0,046	0,022*	0,067	0,021*	0,075	0,022*	0,060
β (Rm-Rf)	0,706***	0,000	0,758***	0,000	0,758***	0,000	0,755***	0,000
β SMB			0,150***	0,000	0,147***	0,000	0,143***	0,001
β HML			-0,109***	0,000	-0,097***	0,003	-0,091	0,101
β MOM					0,026	0,294		
β RMW							-0,072	0,341
β CMA							-0,154**	0,019
Adj. R^2	70,54%		71,18%		71,18%		71,27%	
N	1287							
Outliers removed	3							
Sample of funds	1							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

On the other hand, for the rest of the European open-end impact funds (the Belgian, French, German and Luxembourg impact funds; Tables 4 to 7, pp. 32-33), the generalized alphas were non-significantly different from zero at 10%, 5% and 1% confidence level. Performance aligned with the market could, therefore, be concluded, after reviewing the goodness of fit of the models, hereafter:

First, for the **Belgian funds** (Table 4, p.32), the observations are for one open-end impact fund and 1286 historical daily returns. The adjusted R squared, depicting the goodness of fit of the models, only predicts 58% of the observations. The performance results are then to be considered carefully. The parameters of the models are B.L.U.E., as the model complies with all of the OLS assumptions, after removing three outliers in the data sample (Annex 2, p.58).

Secondly, for the **French funds** (Table 5, p.32), the regression is based on one open-end impact fund and 1284 observations of historical daily returns. The goodness of fit is better than for Belgian funds, with adjusted R squared of 86% for the CAPM and 88% for the Fama-French 3F, Cararth, and Fama-French 5F models. The models all comply with the OLS assumptions, after screening for five extreme values in the time-series data (Annex 2, p.59).

Thirdly, for the **German funds** (Table 6, p.32), the results are derived from one open-end fund and 1286 time-series observations. The adjusted R squared is lower than for other regressions, with 45,5% for the CAPM, 46% for the Fama-French 3F and Cararth models and 47% for Fama-French 5F model. Three outliers were removed from the data sample, enabling compliance with the assumptions of the OLS regressions, on a graphical basis (Annex 2, p.60).

Finally, for the **Luxembourg funds** (Table 7, p.33), a total of 12 open-end funds were considered and equally aggregated for each period to 1289 historical returns observations. The goodness of fit is the lowest among all result, with a 21,93% for the CAPM, 37% for the Fama-French 3F and Cararth models and 38% for Fama-French 5F model. Only one extreme value was removed from the data sample. Graphically, the models comply with the assumptions of the OLS regressions (Annex 2, p.61).

Table 4: OLS regression on Belgian funds with BEL20 index

	CAPM		**Fama-French 3-Factor**		**Cararth 4-Factor**		**Fama-French 5-Factor**	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	0,010	0,538	0,007	0,636	0,008	0,610	0,006	0,693
β (Rm-Rf)	0,725***	0,000	0,770***	0,000	0,771***	0,000	0,763***	0,000
β SMB			0,131***	0,008	0,135***	0,006	0,122**	0,015
β HML			-0,112***	0,005	-0,125***	0,004	0,073	0,321
β MOM					-0,027	0,417		
β RMW							0,111	0,269
β CMA							-0,306***	0,000
Adj. R^2	57,52%		58,01%		58,00%		58,44%	
N	1287							
Outliers removed	3							
Sample of funds	1							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

Table 5: OLS regression on French funds with CAC index

	CAPM		**Fama-French 3-Factor**		**Cararth 4-Factor**		**Fama-French 5-Factor**	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	0,008	0,405	0,004	0,618	0,005	0,581	0,005	0,595
β (Rm-Rf)	0,803***	0,000	0,854***	0,000	0,855***	0,000	0,850***	0,000
β SMB			0,101***	0,001	0,106***	0,001	0,091***	0,005
β HML			-0,313***	0,000	-0,324***	0,000	-0,283***	0,000
β MOM					-0,024	0,191		
β RMW							-0,039	0,490
β CMA							-0,133***	0,007
Adj. R^2	85,91%		87,88%		87,88%		87,92%	
N	1285							
Outliers removed	5							
Sample of funds	1							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

Table 6: OLS regression on German funds with DAX index

	CAPM		**Fama-French 3-Factor**		**Cararth 4-Factor**		**Fama-French 5-Factor**	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	0,021	0,235	0,021	0,227	0,023	0,195	0,025	0,154
β (Rm-Rf)	0,528***	0,000	0,492***	0,000	0,494***	0,000	0,476***	0,000
β SMB			-0,180***	0,003	-0,168***	0,005	-0,227***	0,000
β HML			-0,233***	0,000	-0,267***	0,000	-0,229***	0,006
β MOM					-0,071*	0,056		
β RMW							-0,294***	0,009
β CMA							-0,419***	0,000
Adj. R^2	44,53%		45,81%		45,92%		46,69%	
N	1287							
Outliers removed	3							
Sample of funds	1							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

Table 7: OLS regression on Luxembourg funds with LUXXX index

	CAPM		Fama-French 3-Factor		Cararth 4-Factor		Fama-French 5-Factor	
	Param.	Sig.	Param.	Sig.	Param.	Sig.	Param.	Sig.
α	0,020	0,383	0,024	0,258	0,023	0,275	0,028	0,173
β (Rm-Rf)	0,373***	0,000	0,292***	0,000	0,293***	0,000	0,282***	0,000
β SMB			-0,901***	0,000	-0,905***	0,000	-0,936***	0,000
β HML			-0,325***	0,000	-0,310***	0,000	-0,258***	0,009
β MOM					0,032	0,466		
β RMW							-0,276**	0,036
β CMA							-0,515***	0,000
Adj. R^2	21,93%		36,57%		36,55%		37,39%	
N	1290							
Outliers removed	1							
Sample of funds	12							

*, **, *** = Significantly different from zero at a 10%, 5%, 1% level respectively

MAIN FINDINGS FROM THE RETURN EMPIRICAL RESULTS

To sum up, the performance of **US open-end impact funds** was significantly different from the market returns at a 5% confidence, with an average Jensen's alpha of -1,3% for all the models, precisely -1,29% in the Fama-French 5-factor model, which had the largest explanatory power at 93,70%. The performance of **European open-end impact funds** was not significantly different from the market rate of return at a 1% confidence level, except for the Netherlands. The Dutch open-end impact funds presented significant Jensen's alpha at a 10% level for the most specified model (71,27%), the Fama-French 5-factor model, at an average value of 2,23%.

6.2 RISK ANALYSIS EMPIRICAL RESULTS

The risks analysis assessed the volatility of open-end impact funds relative to the market. The method investigated the level of risk over the period and at the end of the time range as well as the long-run variance of the funds. The metrics were then compared with those of the market benchmark (Section 5.4, p.26).

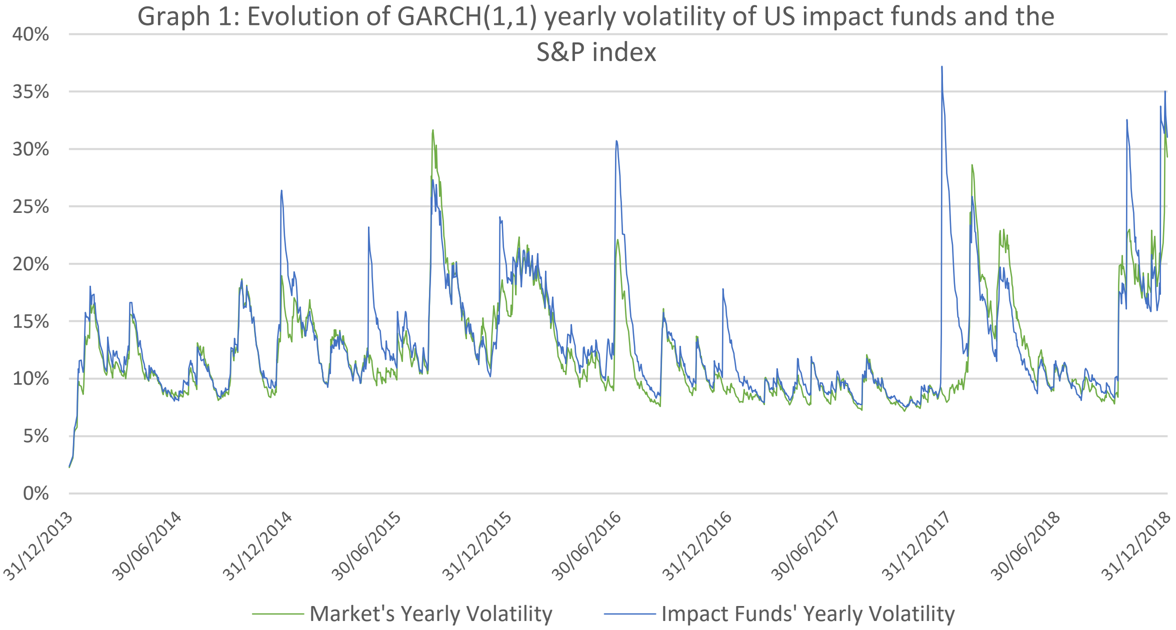
For the **US open-end impact funds** and the S&P index (Table 8), the volatility of the impact funds was computed as higher as those of the market for each of the models. That difference in volatility was low, below 1% for the standard deviation and GARCH(1,1) long-run volatility, at 0,98% and 0,64% respectively, and slightly higher for the EWMA volatility at 2,08%.

The evolution in variance following GARCH(1,1) volatility (Graph 1) was not constant over time. The impact funds volatility curve illustrates frequent ups and downs, mostly aligned with the market. The impact funds volatility peaked at 37,20% on the 21-12-17 while for the market largest spike was at 32,83% on the 27-12-18. The impact funds volatility was greater than those of the market on 70,21% of the observations, with the largest differences in the 21/12/17 – 27/12/17 period with up to 28,36% difference.

Table 8: Volatility estimates of US funds with S&P index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	14,061%	29,815%	14,196%
Market benchmark (Rm)	13,084%	27,731%	13,558%
Rp-Rm	0,977%	2,084%	0,638%

Graph 1: Evolution of GARCH(1,1) yearly volatility of US impact funds and the S&P index



For the **European open-end impact funds**, the results were split among the national and their respective benchmarks. For the France, Germany and Luxembourg, the results were similar to the US, yet more pronounced, with larger variances experienced by the impact funds than by their market benchmarks.

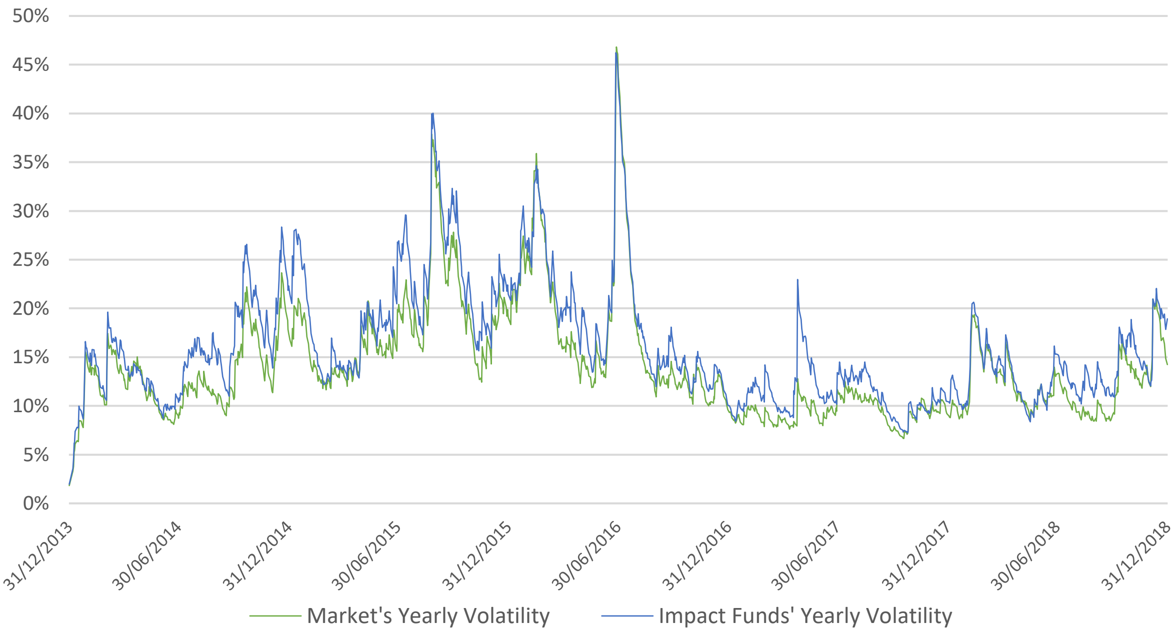
In **France** and the CAC index (Table 9), the gap in volatility between the impact funds and the market was above 1% for the three metrics, with an impact fund volatility greater than those of the market by 2,12% for the standard deviation, by 3,71% for the EWMA and by 1,29% for GARCH(1,1) long-run volatility.

Overall, the evolution of the GARCH(1,1) volatility of the impact funds in the 2014-2018 period (Graph 2) was aligned with the market with both their largest peaks at 46,22% and 46,82% on the 27-06-16 and the 28-06-16, for the impact funds and the benchmark respectively. The volatility of funds was greater than the volatility of the market for 92,86% of the observations. Largest differences in volatility occurred in the 25-04-17 – 28-04-17 time range with 8,49% to 10,17% differences.

Table 9: Volatility estimates of French funds with CAC index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	17,268%	18,470%	17,797%
Market benchmark (Rm)	15,151%	14,764%	16,510%
Rp-Rm	2,117%	3,706%	1,287%

Graph 2: Evolution of GARCH(1,1) yearly volatility of French impact funds and the CAC40 index



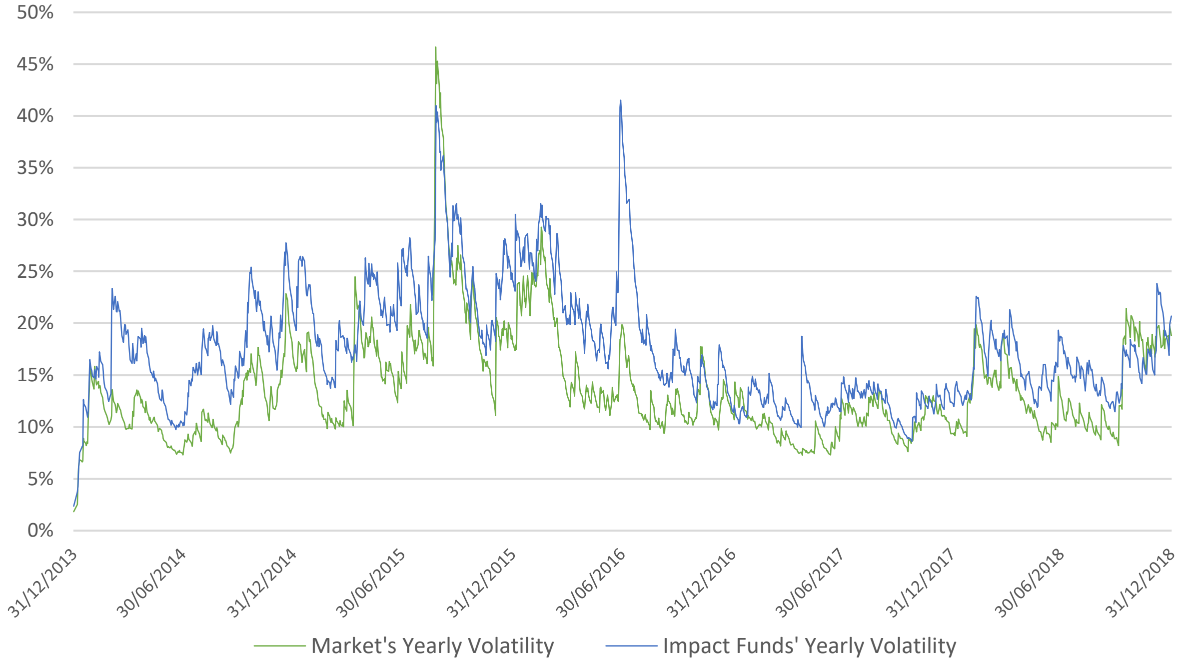
In **Germany** and the DAX index (Table 10), while the divergence of the impact funds volatility relative to the market volatility was relatively small for the EWMA volatility, of 0,22%, the difference for GARCH(1,1) long-term volatility measures skyrocketed to 8,19%. For the EWMA, the differential was of 3,42%.

The GARCH(1,1) variance in the 2014-2018 period (Graph 3) progressed in line with the market, yet the gap between the two was more pronounced. The impact funds volatility reached a spike 40,98% on the 26/08/15. The market, in the same period, experienced strong volatility with up to 46,65% on the 25/08/15. The impact funds also rose sharply at 41,52% on the 28/06/16. On average, the impact funds were riskier than the market for 91,62% of the observations, with the largest differences in volatility from 17,72% to 22,96% occurring in the 27-06-16 – 01-07-16 time range.

Table 10: Volatility estimates of German funds with DAX index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	17,845%	18,802%	24,702%
Market benchmark (Rm)	14,427%	18,579%	16,510%
Rp-Rm	3,418%	0,223%	8,192%

Graph 3: Evolution of GARCH(1,1) yearly volatility of German impact funds and the DAX index



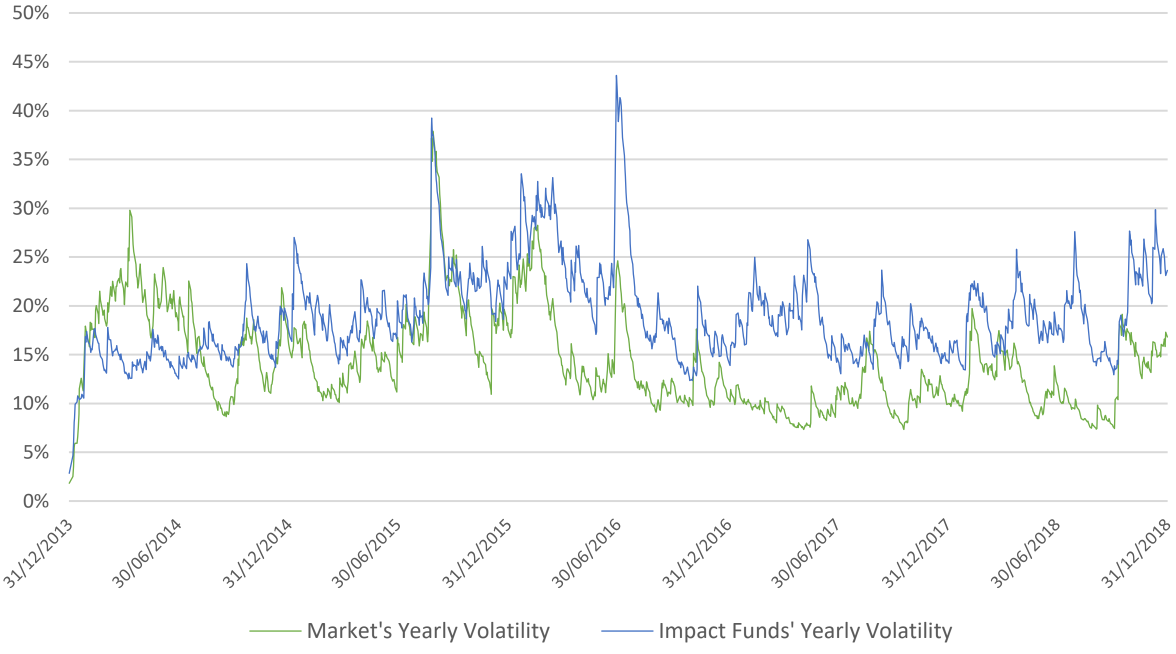
For **Luxembourg** and the LUXXX index (Table 11), the divergence in returns was the most pronounced, with much higher risks for impact funds than for the LUXXX index. The standard deviation was found 3,86% higher for impact finds than for the market, the EWMA volatility of impact funds was 7,44% higher and the GARCH(1,1) long-run volatility was even higher at 8,93%.

Regarding the GARCH(1,1) volatility evolution over the period, (Graph 4), the correlation of the impact funds with the benchmark seemed less pronounced than the previous peers analyzed. The market's stronger spike in volatility was at 37,89% on the 28-08-15. The largest peak of impact funds volatility occurred at 43,60% on the 28-06-16. In the same period, the market volatility, however, lagged, with a volatility of 23,62%. In general, the volatility of the impact funds was higher than the volatility of the market for 84,87% of the observations. Largest differences in volatility occurred on the 28-06-16, as just mentioned, with a 19,98% gap that day, in the 05-07-16 – 05-07-16 time range with 18,70% to 19,28% gap in volatility and on the 12-05-17 with 19,01% divergence.

Table 11: Volatility estimates of Luxembourg funds with LUXXX index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	18,856%	23,291%	25,439%
Market benchmark (Rm)	14,998%	15,848%	16,510%
Rp-Rm	3,858%	7,444%	8,930%

Graph 4: Evolution of GARCH(1,1) yearly volatility of Luxembourg impact funds and the LUXXX index



For the Belgian and Dutch funds, the results were less homogeneous. While the impact funds were found to have higher risks than the market by the standard deviation and the EWMA approach, the GARCH(1,1) metric showed the opposite with less risky impact funds.

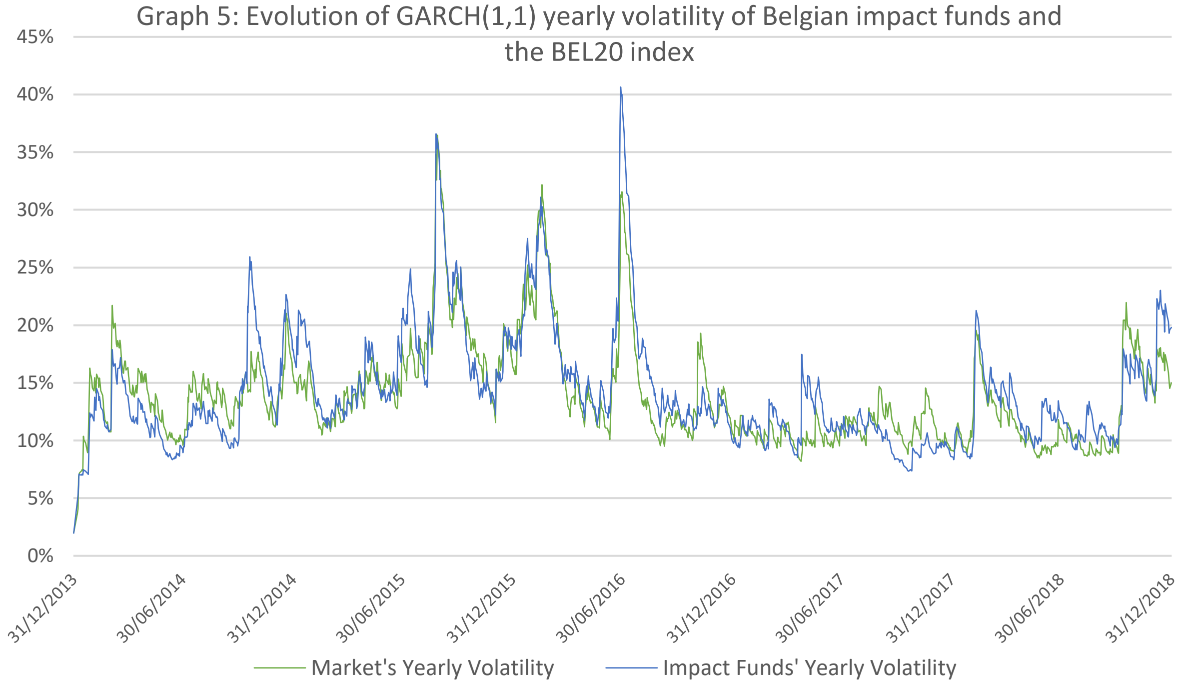
In **Belgium** and the BEL20 index (Table 12), the volatility of the impact funds compared to the BEL20 index was slightly higher for the standard deviation computations at 0,72%, and larger for the EWMA volatility at 4,77%. However, the GARCH(1,1) long-term volatility indicated contrary results with smaller volatility for impact funds than for the market by 0,41%.

Overall, the evolution of the GARCH(1,1) volatility of the impact funds over the 2014-2018 period (Graph 5) was aligned with the market. On the 28-06-16, impact funds volatility topped at 40,65%. Second largest spike was at 36,59% on the 26-08-15. In the same period, the market volatility experienced its largest summit at 36,47% on the 28-08-15. From the observations, impact funds volatility was higher than those of the market in 53,69% of the scenarios. Largest deviations were between 8,80% and 12,44% in the 27-06-16 – 29-06-16 time range and at 11,50% and 10,56% on the 20-10-14 and 21-10-14 respectively.

Table 12: Volatility estimates of Belgian funds with BEL20 index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	14,874%	19,466%	17,797%
Market benchmark (Rm)	14,150%	14,696%	18,208%
Rp-Rm	0,724%	4,770%	- 0,411%

Graph 5: Evolution of GARCH(1,1) yearly volatility of Belgian impact funds and the BEL20 index



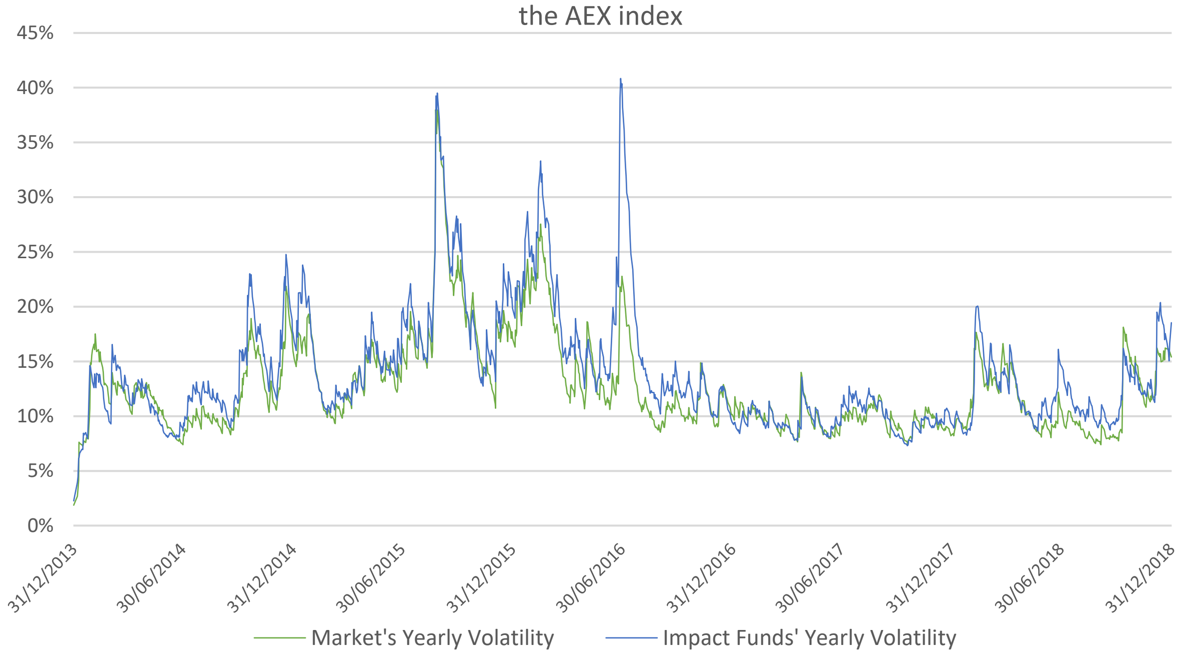
For the funds in **the Netherlands** with the AEX index (Table 13), the standard deviation and the EWMA found higher volatility for the impact funds by 2,50% and 3,30% respectively, than for the market benchmark. Nevertheless, the GARCH(1,1) long-run volatility, depicted substantially lower volatility for the impact funds than for the market, by 3,32%.

The evolutions in variance following GARCH(1,1) (Graph 6) had similar shapes for the impact funds and the markets. The impact funds volatility reached its largest peak at 40,84% on the 28-06-16 funds. In that period, the volatility of market lagged at a maximum of 22,76% on the 30-06-16. The second summit of impact funds volatility was at 39,50% on the 28-08-15. The largest spike of the market volatility was attained in that same period, at 38,00% on the 25-08-15. In general, impact funds volatility was greater than those of the market for 73,55% of the observations, particularly in the 27-06-16 – 01-07-16 time range where the volatility gap reached 15,89% to 19,22%.

Table 13: Volatility estimates of Dutch funds with AEX index

	Standard deviation (yearly)	EWMA volatility (yearly)	GARCH(1,1) long-term volatility (yearly)
Impact funds (Rp)	15,464%	17,905%	13,558%
Market benchmark (Rm)	12,962%	14,608%	16,877%
Rp-Rm	2,503%	3,297%	- 3,318%

Graph 6: Evolution of GARCH(1,1) yearly volatility of Dutch impact funds and the AEX index



MAIN FINDINGS FROM THE RISK EMPIRICAL RESULTS

To sum up, both the US and European open-end impact funds showed higher volatility of the impact funds than of the market benchmark from 2014 to 2018.

In the US, the gap in volatility of impact funds relative to with the market was at 0,98% for the standard deviation, 2,08% for the EWMA and 0,63% in the GARCH(1,1) long-run volatility. The volatility of impact funds was higher than those of the market in 70,21% of the observations.

In Europe, open-end impact funds presented volatilities higher than the market for all of the models, except in the Netherlands and Belgium where the GARCH(1,1) long-run showed the opposite. On the one hand, In France, Germany and Luxembourg, the results homogeneously indicated higher risks for the open-end impact funds industry than for the market. The largest gaps in volatility were computed for Luxembourg impact funds, at 3,86%, 7,44% and 8,93% for the standard deviation, EWMA, and GARCH(1,1) models respectively. Impact funds in Germany indicated a similar magnitude in the differentials, except for a lower EWMA volatility gap at 0,22%. From the GARCH(1,1) evolution of the volatilities, the higher volatility of impact funds was confirmed for most of the observations with the largest frequency for the French impact funds, at 92,86%, followed by German (91,62%) and Luxembourg impact funds (84,87%). On the other hand, for the Netherlands and Belgium, the high variances of impact funds were supported by the models except for the GARCH(1,1) long-run variance. While the standard deviation and EWMA metrics were gradually comparable to their peers, the GARCH(1,1) long-run volatilities were measured at -3,32% and -0,41% for the Netherlands and Belgium respectively. From the evolution of the GARCH(1,1) volatilities, high volatilities of funds compared to the market were attained in 53,69% of the observations in Belgium and 73,55% for the Netherlands, lower frequencies than their peers.

7 CONCLUSION

The thesis aimed to answer the research question: *"What are the risks and return of open-end impact funds in the USA and Europe over the period 2014-2018?"*. Two hypotheses were evaluated: (1) the financial performance of open-end impact funds is aligned with the market; (2) the volatility of open-end impact funds is aligned with the market.

To answer the research question, a description and inventory of the impact funds industry were first drawn, enabling to widen the understanding of the industry. Secondly, the existing researches on the risks and returns of impact funds were reviewed, allowing to sum up the current conclusions on the matter. Thirdly, the major researches on risk and returns on mutual funds were listed, providing a comparison base for the establishment of the methodology of the thesis. Fourthly, the data and methodology were selected and described, as well as the underlying concepts, models, and limitations. By using longitudinal data, the returns were analyzed through Jensen's alpha (1968) and its generalization, the Fama-French three-factor model (1992, 1993), Cararth four-factor model (1997) and Fama-French five-factor model (2015), supplemented by simple and multiple ordinary least squares linear regression, with the method enter. The risks were analyzed through the standard deviation of returns, as well as the EWMA, and the GARCH(1,1) variance. Finally, the computations were realized, through SPSS and self-developed tools in Excel, and the results were obtained and transcribed.

From the risk-return analysis of open-end impact funds over the 2014-2018 period, the thesis enabled to finds the following results:

On the one hand, the **US open-end impact funds analysis** presented a performance which was significantly different from the market returns at a 5% confidence level whereas the risk of the impact funds was found to be higher than the risk of the market. From the models tested, the performance of impact funds relative to the market returns, after risk adjustments, was of -1,3%. More specifically, the Fama-French 5-factor model – the one with the largest explanatory power of 93,70% – depicted an average Jensen's alpha of -1,29%.

The volatility computation for the US open-end impact funds from 2014 to 2018 showed a higher volatility of the impact funds than of the market benchmark, with 0,63% and 0,98% difference in the GARCH(1,1) long-run volatility and standard deviation models respectively and 2,08% for the EWMA. From the progression of the GARCH(1,1) volatility over the 2014-

2018 timespan, the riskiness of impact funds relative to the market was supported by 70,21% of the observations. In overall, the GARCH(1,1) volatility curves of the market and impact funds were aligned.

On the other hand, the results of **European open-end impact funds** although not unanimous, tended to indicate performance aligned with the market as well as larger variances experienced by the impact funds than by their market benchmarks. The Jensen's alphas were non-significantly different from zero at a 1% confidence level, indicating no significant difference in performance with the market after risks adjustments, except for the Netherlands. The Dutch open-end impact funds showed a significative divergence relative to the market at a 10% level the Fama-French 5-factor models, which was the one with the largest explanatory power at 71,27%. Average Jensen's alpha indicated an outperformance tendency of Dutch impact funds, at 2,23% for the Fama-French 5-factor models.

From the volatility analysis of European open-end impact funds over the 2014-2018 period, while the funds in France, Germany and Luxembourg funds indicated larger risks of the open-end impact funds relative to their markets, the funds in the Netherlands and Belgium showed the same outcomes with the exception an opposite conclusion regarding the GARCH(1,1) long-run volatilities. For France, Germany and Luxembourg, higher volatility of impact funds was confirmed by the standard deviation, EWMA and GARCH(1,1) long-run volatility, with a difference of up to at 8,93% computed for the GARCH(1,1) long-run volatility in Luxembourg. The evolution of the GARCH(1,1) volatility over the 2014-2018 period showed higher volatility of impact funds in 92,86%, 91,62% and 84,87% of the observations for the French, German and Luxembourg open-impact funds respectively. For the Netherlands and Belgium, higher risks of impact funds were computed by the standard deviation and EWMA models. The GARCH(1,1), however, indicated the opposite conclusion with lower volatilities of impact funds by 3,32% and 0,41% for the Netherlands and Belgium respectively. The evolution of the GARCH(1,1) volatilities indicated higher volatilities of funds than of the market at a 53,69% frequency in Belgium and 73,55% in the Netherlands, both lower frequencies than their peers.

From the theoretical base of the thesis, a performance either below or aligned with the market as well as a level of risk higher than the market seemed coherent. On the impact investing industry, the returns of impact investment were indeed characterized by the OECD (2015) as ranging from the MRR to capital preservations. Indeed, some impact investments, named "concessionary impact investment" by Burckart (2015, p. 4) purposely targeted returns below the market rate of return, as a trade-off for the social and environmental created. From the open-end funds perspective, the mutual funds themselves were found by many authors to have performance either aligned with the markets or not. Their outperformance is still a matter of debate among academics. The performance results of the thesis could thus be influenced by the type of instrument, the mutual funds, and its industry characteristics, the impact investing industry.

Regarding the risks, the high level of volatility in the open-end impact funds industry could be explained by a large array of risks, either specific to the sector and the instrument, or enhanced on the industry, as detected by Barby and Gan (2014) and further developed by Chappini (2017) and the GIIN (2019a). In the GIIN annual survey (2019a), impact investors were found to experience strong business model and execution management risks, as well as country and currency risk, and liquidity and exit risk (GIIN, 2019a). On the impact funds specifically, Chappini (2017) indicates a concentration risk, which could also be a possible explanation of the high volatility despite the aggregation of returns at a national level. Moreover, seeking impact in addition to seeking financial performance, and thus searching the maximization of blended value, could also be a source of increased volatility.

To conclude, from the developments of the thesis, the research question can be answered by the two following statements:

1. "*The returns of US open-end funds were significantly different from the market over the 2014-2018 period, while, in overall, the European open-end funds significantly performed in line with the market rate of return*."
2. "*Open-end impact funds tended to have higher volatilities than those of the market, both in the USA and in Europe, over the 2014-2018 period*."

To go further, possible extensions of the thesis include a qualitative screening of the impact funds, reducing the bias of the dataset and crossing different databases, using other models, and testing for the significance of the results of the risk analysis, by testing for the difference in variance for each of the methods.

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