Essays on Financial Technologies

by

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Abstract

The four essays contained herein this study focus on recently emerged questions in the field of Financial Technology (FinTech). This new finance domain has a growing importance in the finance discipline, policy, and practice. The FinTech is the common theme, while the thesis is organised to investigate the open questions separately in the essays.

The first essay assesses the required human capital in FinTech. Recent technological developments have enabled a wide array of new applications in financial markets, e.g. big data, cloud computing, artificial intelligence, blockchain, cryptocurrencies, peer-to-peer lending, crowdfunding, and robo-advising, inter alia. While traditionally comprising of computer programs and other technology used to support or enable banking and financial services, the new FinTech is often seen as enabling transformation of the financial industry. A more moderate and critical view suggests that for the full transformative potential of FinTech to be enabled, there is a need for an updated educational curriculum that balances knowledge and understanding of finance and technology. A curriculum that provides a skill portfolio in these two core components and complements them with applied knowledge. This essay also makes an inquiry into the educational curriculum in finance and technology, aiming to inform this modern educational agenda, and into the skills shortages, as identified by firms and experts with examining some of the first educational programmes in FinTech.

The second essay investigates the relationship between financial literacy and attitudes to cryptocurrencies, using microdata from 15 countries. The financial literacy proxy exerts a large negative effect on the probability of currently owning cryptocurrencies. The financially literate are also more likely to be aware of cryptocurrencies, and less to own them due to their price volatility. In addition, data from a second survey of retail investors in three Asian countries is used to externally validify the financial literacy proxy and findings. I show that the relationship between financial literacy and attitudes to cryptocurrencies is moderated by a different perception of the financial risk involved in cryptocurrencies versus traditional investments by the more financially literate. The findings shed light on the demand for cryptocurrencies among the general population and suggest has been largely driven by unsophisticated investors.

The third and fourth essays are closer in their empirical investigation of asset price timeseries data. In the third essay, I assess the bitcoin futures introduction into the retail investor driven marketplace. Bitcoin futures were introduced in December 2017 as an effort to provide institutional and retail investors with additional trading tools for bitcoin. This study analyses the bitcoin Futures mid-quote data from CBOE, and Bitcoin market index applying VAR and VECM process methodologies, Hasbrouck's information share and the Gonzalo-Granger component share measurement to examine price discovery in bitcoin

markets. The results drawn on the intra-day prices show that the futures are leading the price discovery at different frequencies even with comparably low futures trading volumes. The empirical results support the extant literature of futures-spot market price discovery and the role of informed traders in the futures market.

Finally, the fourth essay attempts to evidence the network externalities on digital assets using exchange-listed Initial Coin Offerings (ICOs) data. Utilising an online database comprising of self-reported ICO characteristics, measures of post-ICO performance, along with information on business social networks, higher fundraising figures are found to contribute positively to the ICO long-term success. This positive impact is multiplied by six times when fundraising is conducted to an existing, proprietary blockchain. This large impact is explained by the network effect. The modified information ratio measure is introduced to approximate the comparative quality signalling of ICO organisations using price timeseries and benchmarking these to already functioning blockchain technology, e.g. ethereum in the long-term. The ICO sample's mean trading period on an exchange is 1.5 years and is used for long-period asset analysis. Additionally, the cointegration to the market technology benchmark is found to have a large, significant negative effect on long-term ICO organisational success as this indicates lower ICO intrinsic value.

The final concluding chapter summarises the thesis contribution, implications and a selection of future research avenues relating to FinTech research sub-field.

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Acknowledgements

“*Only* fools rush in”

~ Alexander Pope

“I have concluded that all drinking, water alone too, is harmful. The only exception is coffee.”

– Minna Canth

“Omnia mea mecum porto”

– Cicoro

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Author’s Dedication

I dedicate this work to my family and my friends who have supported me whatever I have decided to do.

Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Signature:

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Chapter 1: Introduction and Motivation

1.1 *Introduction and Motivation*

This introduction discusses the motivations behind selecting the specific topics in this study. The aftermath of 2007-2008 financial crisis expediated the change of skill requirements in banking by increasing a demand for scalable technology. The crisis intensified the need of banks to cut costs and streamline their services with technology made an opportunity for FinTech. Empirical research in FinTech can help understand novel innovations in the context of financial services. Therefore, this thesis asks if these new technologies are conducive to more efficient financial markets, as well as substituting and creating new ways to conduct financial services. The essays consider the current and the future potential of these technologies which are internet based, such as blockchain instruments. The crisis also highlighted that banks were poorly supervised with taking exuberant leverage provisions and had shifted the baseline of the career opportunities in finance. The financial crisis aftermath made notably difficult the job market for people with low technology skills. Banks had moved their demand in human capital moving toward the technology direction. This can be seen in the Google trends data as an exponential rise in open banking searches through and after the 2008-2009 period.

Figure 1.1 demonstrates the technology push and demand pull interaction in financial services. Notably, the financial crisis seemed to be the catalyst for a faster technology adaptation. Whilst technology enables generally, its application to problem solving drives the innovation and adaptation. With this there was also change in the demand for skills and human capital requirements in the banks that were leaning more toward technological skills. This motivated to look further in the empirical evidence of the trends of the skills required in financial services. In conjunction with the human capital requirements for a technology-enabled financial sector, this thesis attempts to assess cryptocurrencies, which are blockchain-based technology applications in financial services. In recent years, the continuing discussion ranging between opposing extremes surrounding the support for and against cryptocurrencies, motivated this thesis to provide an empirical investigation in the demand for these technologies. This discussion includes the heterogeneity of views of traditional consumer and investment banks how to work with cryptocurrencies and draw regulation of these novel instruments into discussion. Whilst these views vary, this also might be perceived to be an incumbent action to emphasise the requirements for regulation to stop or delay upending the financial services marketplace. The paper discusses business strategy and advantages of smaller organisations for innovation in chapter 5.

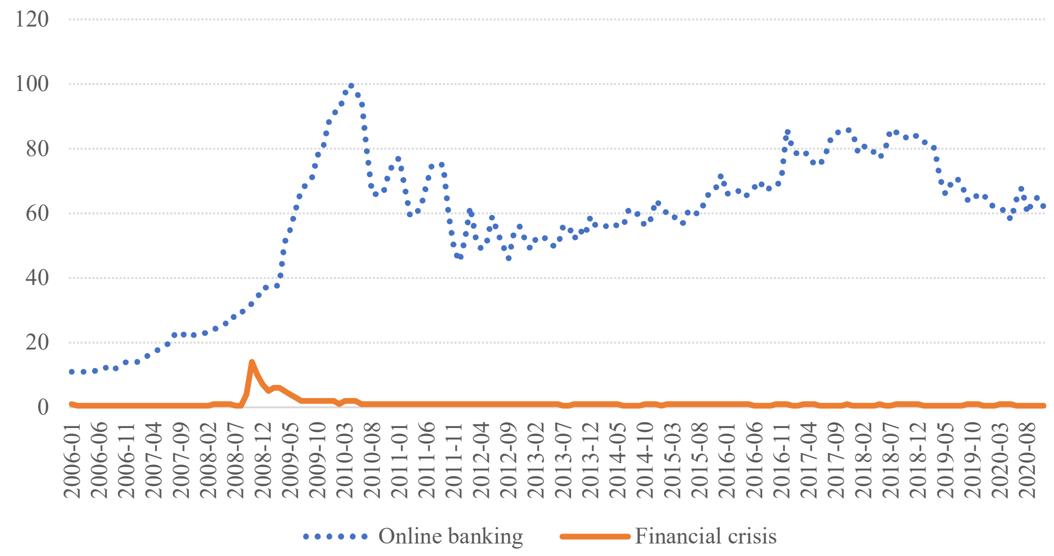

Figure 1.1 Technology push and demand pull

This Figure shows the dynamics of technology push and demand pull indicator. The figure shows the comparative number of research entries by topic. It illustrates that financial crises precede the acceleration of interest in online banking and it indicates that the crisis contributed to this increase of interest. Source: Google Worldwide research entries by topic in the Google Trends.

Figure 1.2 shows comparatively strong, continuing global interest in cryptocurrencies over other financial technologies that were considered for research areas. To this end, cryptocurrencies are first inspected through the lens of financial literacy framework. Whilst higher financial literacy contributes to the individuals' familiarity of available investment products, they might also consider these unsuitable due to high risk. This will have an impact on the demand of cryptocurrencies. Nevertheless, as cryptocurrencies are a global phenomenon, the study inspects through an international setting where motivations may change for attitudes toward cryptocurrencies. For instance, some countries show high local currency exchange price fluctuations. Also, the access to trading cryptocurrencies may only need a mobile device in which this makes it more inclusive for consumers. What follows is the analysis of the cryptocurrency cash market and futures market microstructure by using price discovery time-series analysis. To understand more about this new market, including about its efficiency, it was compared to the established and regulated futures market. Lastly, a fundamental value driver, the network effect, is used to assess the demand in initial coin offerings (ICOs).

The essays use separate datasets. Essay I is a scholarly inquiry comprising a literature review and based on descriptive analysis from the data in other survey-based papers. Essay II uses state-of-the-art micro data, collected via custom household surveys by the ING and the OECD, which are novel and used for the first time.

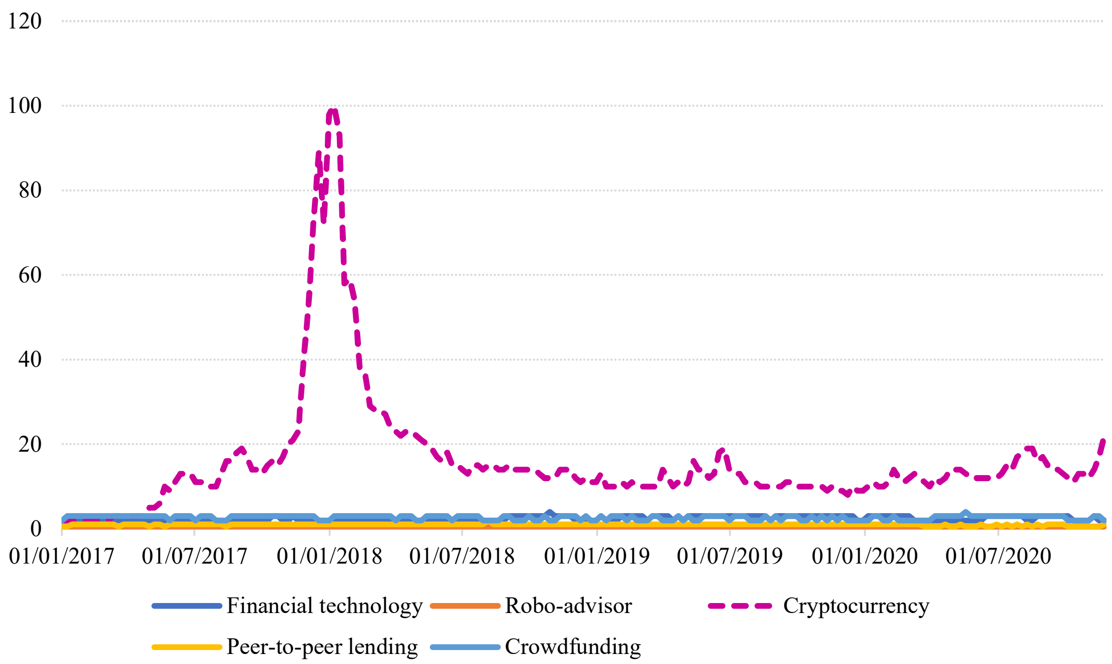

Figure 1.2

FinTech interest topics globally. This figure shows the comparatively high, continuing interest in cryptocurrencies worldwide. This figure also seeks to explain the decision to focus on this topic in this thesis. Source: Worldwide Google research entries by topic. Google Trends.

Essay III uses high-frequency time-series data. Essay IV uses large batch of timeseries and custom data from internet and social media, obtained using big data analytics methods. STATA was utilised for survey data analysis, whilst R was used for timeseries or keyword frequency analysis and Python was used for data acquisition online. The different methodologies in this thesis are purposefully applied to calibrate research methods into the FinTech research. Also, high frequency, i.e., intra-day data, and machine learning methodologies such as classification and regression trees were used for data pre-analysis and validation.

The first essay in chapter 2 looks at skills in financial services relating to technology. This section's central research question discusses the employer's skills demand survey with literature review on how academia is responding to the skills shortage in information technology in financial services. There is a discussion on the skill portfolio proposal approach for jobs in finance due to the changes in technology. It also emphasises the need for ethical training. When a banking employee is tasked with programming algorithms, the financial services end-client, a household, can become very distant from that activity. This raises the question to be asked: as technology changes in financial services, how does this affect the skills required? The push for using technology in financial services was the cost-cutting after financial crisis. This study aims to contribute to show the need for a portfolio of skills to keep up with continuing technological change in financial services. Financial services through its use of digitalisation and automation is a technologically heavy industry for the information management requirement.

Chapter 3 aims at contributing by making foundational analysis of demand of the new financial products, the cryptocurrencies. Specifically, it does this by investigating using novel survey data to estimate financial literacy level in retail investors who invest in cryptocurrencies. As cryptocurrencies are a global phenomenon and mostly accessible to retail investors, there is a need to approach them as a cross-country comparative study and through a retail investor perspective. The data allows the study to assess 18 countries in four continents. This study contributes to FinTech research by demonstrating that cryptocurrencies can add to financial inclusion, nevertheless cryptocurrency volatility can make them generally undesirable for people with basic financial literacy level. This sub-population is nevertheless more aware of the availability of these financial instruments.

Chapter 4 and 5 studies both use price timeseries as their main data, but at different frequencies and durations. Whilst the cryptocurrency prices are considered volatile and base on the unregulated nature of the instruments or exchanges, the price time series data can be transformed to analysis using methodologies that have been used in traditional finance. If the results were to show statistical insignificant noise, this would have provided support for the critics of digital assets.

Chapter 4 presents the inquiry into the bitcoin futures introduction into the marketplace, and the influence these have for the retail driven markets as whole. In essence, the research compares the older and newer financial innovations with regards to their instrumental efficiency through market microstructure research. Here the price discovery process methods that are commonly used to research market microstructures are utilised. This chapter contributes by proposing that whilst there might have been addition of new technology framework with lower barriers to entry, the more institutional and established financial instrument framework was leading in the market price formation with much lower trading volume. Accordingly, the result indicates where the informed trader can find the leading price and not the lagging price. This also relates to the uncertainty on how cash exchanges may operate in the absent or low regulatory market activities.

Chapter 5 describes the attempt to estimate ICO organisational success relating to the supply side economies of scale, also known as network effects. Network effects are said to drive the value of these digital assets, whilst their impact is not empirically evidenced. This study is motived to investigate their existence and their measurable impact. This would take into account the investor demand, but also user demand. The main research question relates to how to empirically evidence the fundamental value of cryptocurrencies. The follow-on sub-question poses then on how to empirically prove and measure the network effects in these instruments. This chapter aims at contributing to the FinTech research in a multitude of ways. It formalises a comparative price-quality framework from price series and introduces this as modified information ratio. The result estimates evidence of network effects in ICOs. Also, it introduces a cointegration variable that can be used as an auxiliary measure to form a view of ICO's intrinsic value. This is where it can also be acknowledged that these instruments can be perceived to have long-term fundamental value and are not completely driven by short-term sentiment. The idea for the modified information ratio came from the curriculum of Chartered Alternative Investment Analyst (CAIA) charter. The information ratio is derived from Sharpe ratio where the risk-free ratio is substituted with a benchmark to gauge special information (Goodwin, 1998). This information ratio is normally used to assess hedge fund managers relative risk adjusted return within their own peer groups, as different trading strategies have differing return distributions. For instance, bond investing strategy has a left-hand skewed return distribution, whilst equity trading strategies show comparatively more normally distributed returns. When the absolute measures are challenging to use for analysing novel markets, a more cautious approach is to make use of a comparative measure. In the CAIA study material, the information ratio was presented as one of the best industry practice measures to compare alternative investment managers' performances against their own peer group index. For this study, an ICO peer group index was considered, but the preference was to compare performances to a working technology that already exhibits network effects, and thus assumed to incorporate this fundamental value coming from its use rather than its potential.

Finally, following the essays, chapter six concludes by highlighting the thesis contribution and summarising the empirical findings of the research questions. The chapter also includes a discussion on practical and policy implications of the findings, limitations in the studies and potential new avenues and extensions for future research.

Chapter 2: On the Educational Curriculum in Finance and Technology

"We are a technology firm. We are a platform."

– Lloyd Blankfein, CEO Goldman Sachs, 2017

2.1 Introduction

Fintech can be perceived to be an amalgamation of finance and innovative information technology, which can make services and operations more efficient, less costly and enable the provision of new products and services. While traditionally comprising of computer programs and other technology used to support or enable banking and financial services, the new FinTech sector is often seen as entailing disruptive potential to the financial industry and markets. At the same time, employers and experts have identified notable skills gaps to the training and experience of graduates and employees who are likely to be employed in FinTech occupations. Such shortages exist for graduates stemming from both the social sciences, such as finance and business, and the computer science background. The advent of new technologies is changing the skills required by the financial service industry. Importantly, what seems to be missing is the synthesis of balanced and applied programmes, combining multi-disciplinary skills and enabling graduates to cover the gap.

Business schools are the first natural candidates to undertake the delivery of new FinTech methods and respond to market needs. Financial institutions and large international corporations appear keen to engage with educational institutions in identifying market requirements and the desirable skills. It is vital that the new skill requirements are planned to be facilitated via an integrated delivery mode, entailing the essential technical skills in e.g. programming, data management and the development of applications, alongside a solid understanding of the foundations of finance, regulation and ethics. It is indicative that the CFA Institute is suggested to plan to introduce Fintech as a self-alone-standing unit in its 2019 curriculum (Butcher, 2017). While there are already elements of FinTech included in its sections covering trading, private wealth and quantitative methods, the FinTech additions are supported by the views of charter-holder practitioners in the industry (CFA, 2017).

In this chapter, I discuss skill gaps in the financial service industry and assess the current state of the art in FinTech in academia. I also engage in a scholarship inquiry that attempts to identify the relevant elements of a curriculum that might aim to minimise the skill shortage reported by employers. I attempt a primary synthesis from the educational curricula in the two distinct disciplines that need convergence as a result of the "distributed" nature of the internet and the opportunities this might enable for the delivery of financial services. This first inquiry into an interdisciplinary curriculum is by no means exhaustive. Instead, it is intended as an invitation for further scholarship inquiry into academia and knowledge exchange with the experts in finance and information & communications technology (hereafter ICT).

Section two assesses the potential skills gap in FinTech, by presenting and reviewing the relevant managerial and academic viewpoints and offering some insights from the literature on the skill portfolio. Section three assesses the potential for a new educational curriculum in finance and technology, by reviewing the current state of the art in terms of new programmes, and presenting the candidate elements of a synthesis in an interdisciplinary curriculum. Section four presents some critical concluding remarks.

2.2 Fintech and the related skills gap

The FinTech domains that seem to entail the greater potential for ground-breaking applications involve: (a) Banking (Consumer & commercial banking, Consumer lending, Business lending), (b) Payments (Point of sale payments, Payments backend & infrastructure, International money transfer, Consumer payments), (c) Investing (Institutional investing, Equity financing, Retail investing, Crowdfunding), and (d) Infrastructure (Banking infrastructure, Small & medium business tools, Financial transaction security, Financial research and data (Harris, 2017). Personal finance and financial awareness is another domain to which FinTech applications can exert an impact. The financial service industry is a leading user of information technology and these technological developments change the market demand for skills (Bresnahan, et al., 2002).

When the above FinTech product areas are considered, the development of related applications requires technical skills, from statistical analysis and data management to software coding skills, inter alia. FinTech is a field that can benefit from the development of multi-disciplinary skills. For example, a designer of robo-advisor that services a large number of private wealth clients would not only benefit from asset allocation experience but also from skills to design artificial intelligence tools. He/she would also benefit from a solid knowledge of financial regulation and ethics. The review in (World Economic Forum, 2016) highlights that internet, cloud and big data technologies are the most likely candidates to drive change in the financial services. According to (PwC. 2017), there is already a skill shortage in the areas of data analytics and artificial-intelligence innovation. A graduate that holds financial and ICT skills in the skill portfolio would have an advantage in this evolving labour market. It is evident that the financial-service industry is in competition with other industries for the acquisition and further development of related talent. The prediction is that, by 2020, there will be a 9,000,000 skill shortfall in related jobs in Europe (Cedefop. 2015). Apart from the growth in the business and finance vacancies, driven by emerging financial-service models, there is also increasing need for employees with related management skills (PwC, 2017), e.g. on managing innovation.

When more generic ICT jobs are considered, there is already a lack of high technical skills, which is deemed only to deepen. The Institution of Engineering and Technology Skills and Demand in Industry (2016) confirmed the strong demand for skilled employees in science, technology, engineering, and mathematics (STEM) disciplines. Among organisations hiring in STEM roles, 59% reported lack of practical skills, and 43% mentioned the lack of work experience. There is a widespread agreement amongst the respondents regarding a more balanced and applied skill portfolio, as 91% stated that a better integration between work placements and academic studies would help. 50% of the surveyed representatives reported substantial, and increasing skill gaps amongst their recruits. The skills of recent graduates represent a major challenge, as stated by 62% of the respondents. In close proximity to STEM occupations, the FinTech sector sees similar challenges. It is also the case that the skill shortfall might be even more striking, due to the novelty of the techniques involved, and the seeming lack of a multidisciplinary skill portfolio among the graduates the FinTech sector might be seeking for.

On the demand side, in managerial interviews from the European Company Survey in (Eurofound, 2015), finance was the industry, in which companies perceived to have the least difficulties in hiring staff. However, the same report stated that by the year 2020 there will be a shortage of ICT personnel in Europe and the technological advancement is also contributing to the skill mismatch across industries. The specialist knowledge, especially when involving synthesis of ICT and finance, seems to be an area that has a skill gap. According to (PwC. 2017), the financial-service industry is in rising demand for advanced data analytics skills and knowledge. 72% of the interviewed financial service CEOs were concerned about the skill portfolios of job applicants and 73% of them were concerned about the speed of technological change. Both figures were higher, compared to surveys of previous years.

While CEOs were looking to employ more people in asset and wealth management, it is the case that in the fields of insurance, banking and capital markets CEOs were prioritizing on skills pertaining to digitalisation and technology. Moreover, 83% of the insurance CEOs responded they had anxiety for the speed of technological change and 81% of them had similar feelings toward skills shortages. These figures were increased, compared to figures close to 70% in the previous year. For insurance company CEOs, the development of artificial intelligence is a challenge, but also an opportunity, particularly if it facilitates the current practices.

(CFA, 2017) surveyed how charter-holder members perceived the near-future impactful trends. Big data was thought to have a moderate to significant impact on financial analysis by 81% of respondents, the use of robo-advisors in private wealth had the support of 67% respondents, and the view that investment managers should benefit by having FinTech skills received support by 68% of respondents. Financial analysis, big data analytics, artificial intelligence, machine learning and algorithmic trading are all said to be incorporated into the CFA exam curriculum from 2019 onwards.

On the demand side, the empirical evidence on the consensus regarding the need for new interdisciplinary skills and related training appears solid. The European Skills and Jobs Survey by (Cedefop, 2015: p.75) examines the share of jobs with significant rise in the need to learn new things by industry in the European Union (hereafter EU). The survey results indicate that the financial insurance and real estate services are the second highest among 16 industries. The ICT industry is at the middle of the distribution among industries, but still scores relatively high. However, using the same survey, (Pouliakas, 2016) finds that the top 5 occupational groups with rapidly changing skill profiles are ICT professionals and associate professionals, production or specialist service managers, health professionals, electronic and electronic trades workers/science and engineering professionals. Documenting the share of EU jobs with accelerating task complexity, (Cedefop, 2015: p. 18) shows that financial insurance and real estate services are at the top among 16 industries. 74% of the employees reported a change or increase in the variety of job tasks since they had started their jobs. Examining the drivers of change by industry, World Economic Forum (2016: p. 9) reports that for the financial service industry and the ICT industry, some of the most significant drivers of change were mobile internet and cloud technology, processing power and big data, consumer ethics and privacy issues, the internet of things, the sharing economy and crowdsourcing. Examining the incidence of work-based learning (hereafter WBL), (Cedefop, 2015: p. 16) documents that in finance, business and economics, as well as in other social sciences, some 30% of respondents had received WBL, with the figure in computing sciences being close to 39%. Examining the source of WBL, (Cedefop, 2015: p. 64) documents that 60% of professionals in ICT services received their training only within an education institution, with the figure being 67% for professionals in financial, insurance or real estate services. The figures for formal learning at the workplace were among the lowest for the two groups, at 30% and 31% respectively. The figures indicate the relevance and importance, as well as the challenge at hand, for academic institutions to undertake the training for the new FinTech curriculum.

In the labour economics literature, a skills mismatch is a situation in which there is a discrepancy between the qualifications and skills that individuals possess and those needed by the labour market, i.e. a pillar of labour market mismatch (Cedefop, 2010). Employers are unable to find the right talent, despite offering competitive wages and, as a result, face skill shortages. Skill gaps arise where the skills required are unavailable in the workforce, for example, due to technological advance. Thus, with underskilling (or skill gap), individuals lack the skills and abilities necessary to perform the current job adequately (Cedefop, 2012; 2015). From this perspective, there does seem to be a FinTech skill shortage in the financial industry, as the demand for particular skills exceeds the supply of those skills in the prevailing pay. This is confirmed by CEOs and industry representatives who mention there appears to be a skill deficit among current employees. The skills and abilities of candidates are lower than the new benchmark level of skills that technological innovation and new FinTech applications and promises are setting.

More recent works in the skill-portfolio literature provide evidence for the importance of skills that are acquired via experience and can be applied to different settings (Panos, et al. 2013). Human capital accumulates at the firm level through education, learning-by-doing and learning-by-interacting, but may also be acquired externally (Robinson, 2018). As shown by Shaw (1987), occupational change occurs when there is a positive difference between the present value of the current and an alternative occupational pathway. She illustrates that the degree of transferability of skills across occupations is an important determinant of occupational choice, with a higher degree of transferability being associated with a greater probability of individuals moving to another job. The return to investment in a particular skill is increasing in its subsequent rate of utilisation when investment costs are independent of how acquired skills are employed (Rosen, 1983). The skill-weights approach by Lazear (2009) assumes that all skills are general in nature, but the combination of single skills varies from firm to firm. Thus, specificity can be entailed in any type of occupational training, as only the combination of single skills makes them specific[1].

Geel, et al. (2011) emphasise that the trends in modern labour markets require the distinction between skills and tasks. A task is a unit of work activity that produces output, while a skill is a worker's endowment of capabilities for performing various tasks. The distinction becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labour market conditions and technology (Robinson, 2018). Acemoglu and Autor (2011) link the polarisation of employment to the 'routinisation' hypothesis and explore detailed changes in occupational structure across the US and OECD in view of that framework. Routine tasks are characteristic of many middle-skilled cognitive and routine jobs, such as book-keeping, clerical work and monitoring jobs. Technical advancement in this manner would complement either high skilled or low skilled personnel in their tasks. The supply of labour in the market, e.g. those who have completed their degrees, is deemed being in the "race" with the demand for skill emitting from the changes in the technology (Tinbergen, 1974.). The traditional view on technological progress was that it especially affects the demand for roles that majorly consist of elements of routine tasks (Tinbergen, 1974). These are the middle-level skilled roles. However, when it comes to ICT in the FinTech era, the transition that seems more relevant is that from routine cognitive (and

[1] Following this approach in building occupation-specific skill-weights for Germany, Geel et al. (2011) show that occupation-specific skill portfolios entail higher net costs of apprenticeship training and small occupational change probabilities.

even manual) skills to non-routine cognitive skills, involving primarily analytical, but sometimes even inter-personal, tasks (Aedo et al., 2013). The design of FinTech applications requires both an understanding of finance and high-level technical skills, e.g. in big-data management. These skills can be used to create artificial intelligence enhanced solutions, blockchain applications, cryptography - including smart contract - and financial-service applications on the internet. Such tasks are related to a broad spectrum of financial application, including how paying, investing, borrowing or receiving investment advice is conducted (He, D et al. 2017).

Considering the above background and assessments, it appears that when it comes to the FinTech curriculum, the skill-portfolio approach provides a suitable framework of study. Both managers and employees are aware of the need for new skills and seem to identify the increasing skills gap. Under that prism, it might thus be the case that work-based learning and an occupation-specific FinTech skills learning approach is not the most efficient for either the worker or the firm. Thus, the scope of an updated business school FinTech curriculum is a most important modern endeavour.

2.3 An educational curriculum for a FinTech-skills portfolio

Given the ongoing development of corporate FinTech activity, one can easily infer that a solid relationship between academia and the industry for the training of the next generation of FinTech graduates is in order. This collaboration will aim for enhanced graduate employability, skill transferability and – importantly – the informed development of FinTech applications in directions that are compatible with ethics, regulation and the pivotal targets of client protection and social performance. The latter two are the pillars of responsible banking and finance, a model that aims for the enhancement of financial capability and societal well-being. It is worth remarking the positive role that commercial funders as well as governmental agencies can play to support a better integration between the educational curriculum of universities and training providers and the aims of the financial service industry. Hence, catering to the identified skills gap can and should be seen as an opportunity for rendering FinTech development as conducive to the enhancement of financial capability and societal well-being.

Due to the very recent development of the field, the skills pertaining to the FinTech sector have not yet been organised in a widely recognised supporting body of knowledge to be used by taught programmes. The natural first step in the development of academic FinTech programmes pertains to efforts for the integration of the distinctive disciplines into comprehensive applied programmes. This development can again be seen as an opportunity to enhance the domains of interdisciplinarity, industry-relevance, knowledge exchange, and social impact by the academic programmes of business schools. A large number of existing non-FinTech programmes stems from a single background, i.e ICT, engineering, finance, accounting, business, economics, management or law. The finance and business curriculum is largely unknown in ICT disciplines and an integrated ICT curriculum is largely absent or limited in most finance programmes and business schools. I argue that the approach needed is a synthesis of the educational curriculum in finance and ICT, bringing the two strands together in a more cohesive way. This involves a greater emphasis by business schools on the planning, integration and delivery of courses related to data processing and analytics, programming languages, along with new elements regarding the digital transfer of value, such as blockchain and distributed ledger technologies. Hence, this synthesis of a curriculum must rely on multidisciplinary collaboration between academic experts.

According to EY (2016), businesses that are involved in FinTech would benefit from sourcing skills within the fields of finance, technology and entrepreneurship. A single graduate would not need to possess them all in the skill portfolio, but the richness of a skill portfolio would certainly benefit the individual in this evolving labour market. When looking at the limited existing curriculum offering on FinTech, a lot of the current emphasis is on describing FinTech as a phenomenon, rather than involving the 'hard' core of skills needed in the two domains of finance/business and IT. In this regard and noting the scarcity of formal work-based learning and vocational training in the relevant sectors, the primary FinTech skills would be better attained via university education.

The business schools are natural learning platforms of FinTech due to their expertise in approaching business organisation problems from a multidisciplinary perspective. The curriculum would further benefit from designing the interdisciplinary courses to be more integrated rather than teach them in a 'silo' approach (Smith-Ducoffe et al., 2006). (Navarro, 2008) makes a further claim that knowledge and teaching would need to be de-compartmentalized. Given the task at hand, it is likely that curriculum development might benefit from some experimentation and case studies, involving e.g. the matching of academic pairs from the two primary backgrounds in the delivery of a new applied course that combines finance and its relevant technological applications. Learning can also be advanced through experiential methods, particularly in ICT (Li, et al. 2007), and in collaboration with the industry when it comes to graduate internships and work placements. Li, et al. (2007) also note that business schools have not generally been effective in teaching information systems.

From a management science perspective, a lot of the emphasis of business schools has been on describing the management of innovation or creativity. This expertise renders a natural candidate curriculum that can adapt to the management of the new digital assets, FinTech processes and applications. In support of this argument, Fichman et al. (2014) discuss the need for business students to understand how technology changes businesses or enables process and product innovation. Thus, stemming from the legacy of a number of successful Technology Management programmes, e.g. those of NYU, Columbia, Berkeley, University of California at Santa Cruz, University of Texas at Dallas, LSE, University of St. Andrews, ETH Zurich, and Technische Universität of München, the first two identified components of a modern FinTech offering are redesigned courses on **(a) Financial Information Systems** and **(b) Managing Innovation**, along with any relevant variants.

An inquiry into the recently developed programmes on FinTech reveals a tendency to move fast, in response to industry trends. It is vital that a list of well-defined industry/user requirements is obtained prior to the creation of courses. However, given the uncertainty of any innovation process, it is also the case that such a list is difficult to obtain in a concise manner. Certain programmes have been more innovative than other in their design and very few have emphasized on the essential 'hard' skills in technology. For instance, the MBA programme by NYU's Stern School of Business offers graduate courses in ICT training catering to certain 'hard' skills on e.g. programming and big data analytics. This is also the case with the MSc Fintech programme by the University of Strathclyde, which is probably the first of its kind in the United Kingdom and Europe. Some other new graduate courses on FinTech seem to largely rely on the management-of-technology component. Wharton and Columbia provide FinTech courses as a part of the MBA. MIT provided an online Fintech overview programme run on the Getsmarter educational platform, which was later discontinued. This online programme was focusing on new business model entrepreneurship. Oxford University Saïd Business School also launched an intermediate Finech programme on the Getsmarter platform in Autumn 2017. The course is an overview of the FinTech landscape and the possible applications that can stem from this new landscape. Edinburgh Napier University also provides an intermediate programme on describing the FinTech solutions and the marketplace.

Our own inquiry into the components of the newly established programmes, and some further insights stemming from discussions with representatives of the financial industry suggest a 'hard' skill component in finance, comprising of the following six courses, and related adaptations: ***(c) Investment Portfolio Analysis/Management, (d) Financial Risk Management, (e) Applied Computational/Quantitative Finance, (f) Financial Regulation and Ethics, (g) Fintech Entrepreneurial Finance, (h) Fintech Personal Finance and Financial Planning/Wealth Management***. The computational finance component can be thought to place emphasis on FinTech applications and systematic trading. The FinTech elements of entrepreneurial financial and personal finance are again related to an extensive redesigning of the traditional courses, enabling the incorporation of applications related to e.g. crowdfunding and P2P lending[2], robo-advising, etc. Other elements that can be considered as of high relevance to FinTech applications are **monetary economics**, **international finance**, and **development finance**. However, these elements do not appear in any current offering.

Following a similar review process regarding the ICT component of FinTech programmes, and noting the current limited current offering, I identify the following seven ICT elements, along with their variants: ***(i) Big Data: Systems/ Programming/Management/Analytics, (j) Artificial Intelligence, (k) Machine Learning, (l) Cryptography/Cyber-Security & Forensics, (m) Human-Computer Interaction and Design, (n) Computer Visualisation Methods and Applications,*** *and* ***(o) Blockchain Technology***.

Some of the above components are worth further elaboration. An element that is novel and largely non-existent in the curriculum is that of blockchain technologies. Blockchain

[2] Crowdfunding leverages the internet in reaching out to a larger group of interested parties and enabling them to participate in a new venture with smaller sums of money, either as investors or as early buyers. This funds-pooling technology is mostly used as a new business model, but also for charitable purposes. Moreover, peer-to-peer lending platforms lend to businesses but also to households that require consumer credit or mortgages. These are a new form of intermediary, catering to borrowers over the internet, using algorithms for matching borrowers and lenders, along with associated risk-return profiles.

is considered to be a general-purpose technology, alongside facilitating innovation in electricity supply and the internet, which entails vast potential applications (Catalini and Gans, 2017). Specifically, in financial services, blockchain technology can be used for instantaneous trading and settlement, payments and transfers, and ultimately for record keeping. Blockchain applications can also involve an adaptation of tokens or cryptocurrencies, which are privately issued value-storing methods of exchange over the internet. The blockchain applications are considered as potentially conducive to cost reduction, the efficiency and security in transactions of all sorts. Because of the underlying technology, blockchain sees potential enabling applications beyond finance in areas such as supply chain and inventory management, the creation of national databases on e.g. citizen identification and land registry, and a fraud-proof authentication process for luxury items. In finance research, it is seen as relevant to corporate governance, e.g. in trading corporate securities on the blockchain, central banks and digital currency, sovereign debt management, overseas development assistance, financial inclusion and banking.

The inherent complexity of the blockchain would require an interdisciplinary approach to its course delivery. It engages and involves elements as diverse as peer-to-peer networks, game theory and "crypto-economics", monetary economics, cryptography, cyber security and formal verification, as well as software engineering, programming and software development. Some schools have recently started to introduce blockchain technologies in their curriculum offerings, with a few business, finance, law and, computing departments being the first to offer related courses. As a collaborative effort between NYU's Law School and the Stern Business School, a course on Bitcoin and Cryptocurrencies was among the very first that started in 2014. It was followed by the more technical Bitcoin and Cryptocurrency Technologies course by the University of Princeton, which is also offered online on the massive online open course (hereafter MOOC) platform Coursera. This is also the case with the University of Stanford's course on Bitcoin Engineering. In Europe, few Universities offer blockchain-related courses and programmes, such as the MSc in Digital Currencies at the University of Nicosia, in Cyprus (also available on a MOOC platform), and the more recent undergraduate module on Blockchains and Distributed Ledgers at the University of Edinburgh.

Cryptography can be applied as a part of online software security, trading verification and privacy upholding (Böhme et al. 2014). It is also widely used in the security protocols of blockchain applications. Software security and the subsequent trust that is likely to stem from this feature among users, is an important aspect of any online, or standard, financial service platform. Cryptography can also be applied in designing smart contracts, which are pre-programmed automated contracts through which anonymous peers over the network can transact with each other (Szabo, 1997).

Big Data solutions that can facilitate in enhancing credit analysis or be applied to risk management can also be used for creating machine learning or artificial intelligence tools for asset management (PwC, 2013). Managing Big Data tasks pertains to managing large databases or constantly changing online data, using advanced programming and statistical analysis (McAfee and Brynjolfsson, 2012). These were not available or unfeasible with standard technologies of the recent past (Constantinou, and Kallinikos, 2015). Big data tools are facilitated by the internet and the subsequent surge of available data, but also by the declining price of computing power and data storage. Finally, artificial intelligence can ultimately power scalable financial tools due to its ability to replace expensive human cognitive power (Markus, 2015), or improve the available service or enable the creation of new services. One of these new services is robo-advising, in which artificial intelligence manages the investment portfolio, and can reduce the asset management service fees charged (Lam, 2016).

2.4 Concluding remarks

The review of the previous section is likely to lead to the rhetorical question if the above elements and their related 'hard' skills can be incorporated into a 1-year graduate curriculum. Their mere numbering suggests some 2 generic components, 6 core finance elements, and some 7 ICT domains. Thus, it seems that the answer to the above question, along with the design and duration of FinTech programmes, and the choice of emphasis on either the 'soft' or the 'hard' skills largely depends on the target student audience and their backgrounds. The finance and business graduates and IT/engineering graduates have different skillsets and comparative advantages in learning. One can think of conversion graduate programmes emphasizing on either of the two core components and addressing either of the two student audiences. For instance, an ICT graduate who wishes to obtain a solid knowledge in finance and engage in relevant applications as part of a graduate thesis, would be suitable for a programme that requires advanced ICT knowledge as an entry requirement. This is also the case for a finance/business graduate with some standard ICT knowledge, who wishes to further develop their ICT skills in FinTech applications. Thus, in the case of 1-year MSc programmes, the programme leader would need to conduct some careful market analysis regarding the target audience. Within this rationale, the design of some more advanced programmes of 2 years of duration, such as the MBA programme of NYU Stern Business School, could be regarded as pedagogically more suitable for fewer entry requirements.

Another dimension that could be evident from the above analysis is that the FinTech development offers an opportunity for the generation of joint undergraduate programmes, stemming from an interdisciplinary collaboration between finance and ICT programmes, and their related academic departments. It is likely such joint programmes are already in place in some institutions. However, it is worth emphasizing that what is currently largely missing is the integration between the ICT and the finance curriculum. Another aspect that needs catering to is the enrichment of the joint curriculum with applied courses engaging in the modern FinTech applications. A new FinTech offering would require that the two related educational curricula adapt and evolve. Over time, I would expect a more well-defined body of knowledge to emerge.

A third element worth noting is that the endeavour to initiate new courses, based on either the 'hard' or the 'soft' FinTech components, can be seen as a necessary first step by institutions. Institutions can benefit from own comparative advantage in specializing in courses, instead of a whole programme, and make independent offerings in terms of MOOCs and work-based learning programmes. Thus, even if an institution does not have an immediate comparative advantage in the 'hard' FinTech components or a legacy of strong interdisciplinary collaboration between business and ICT studies, the initiation of some relevant courses on either the 'soft' or the 'hard' core of FinTech could still be a worthy investment. This will also set the foundations for later recruitment, training of the future lecturers, and potential programme development.

In conclusion, rapid developments in technology have led to a number of new financial applications, business models and ways to utilise big data. There is a need for an updated curriculum which addresses the changing needs for skills in the financial services, as identified by employers, employees and professional bodies. Skill gaps are largely technical in nature, but often also involve the lack of economics intuition and the limited understanding of regulation and ethical concerns. Social science and law school graduates, respectively, are typically better trained for these latter capabilities.

Critical thinking should be a primary element in the new curriculum offering. There is also a need for intensified knowledge exchange and transfer between academia and the industry, in the form of initiating scholarship inquiries, sharing and research findings, and embarking on joint apprenticeship and training programmes in applied FinTech. One must also note that published research of excellent quality is currently scarce in FinTech, at least in non-specialist journals, e.g. in the list by the Association of Business Schools (hereafter ABS). For research-led teaching to eventually occur, it would need to be the case that the industry is willing to facilitate academic researchers with information and data, and that universities and related bodies are willing to encourage and invest in research and scholarship activity in FinTech. This dimension should normally precede the initiation of FinTech courses and programmes. Thus, it must not be neglected. I believe that initiating joint research agendas will inform the curriculum, 'train the trainers' and, ultimately help minimise skill mismatches.

As a critical concluding remark for this chapter, one must remark a lesson from recent history. Financial engineering has been integral to the growth and success of mortgage finance, along with the generation of several relevant derivative and securities products. With mortgage flows being inherently complex and volatile, their management required sophisticated financial engineering because of complex embedded options. Securitisation, liability management, derivative instruments, and insurance were the key related tools, which were largely assigned to 'financial engineers', a relatively new specialisation that appeared some years back. Back at the time, and somewhat similarly to the FinTech rapid development, few universities followed the market trends in establishing well-defined financial engineering curricula, in terms of programmes and courses. Very few had the expertise to do so effectively, but almost all business schools eventually started courses related to describing the products. Anecdotally, a large portion of the new employees in financial engineering occupations lacked the social science training, and potentially the sound understanding and intuition around societal dynamics, ethics and regulation. As followed, the mortgage crisis – and the much broader financial-crisis consequences – exposed issues with how far financial engineering had gone, with all its multiple layers, for example, the mortgage loan, complex securitisation in multiple levels, derivatives on the securities, and the new entities investing in the securities and derivatives. The history shows that risks increased at each step due to complexity, leverage, total size of the exposure relative to economy, but also often due to fraud and misrepresentation, and inflexibility to deal with change.

With the finance and business curriculum being largely unknown in ICT studies and the ICT curriculum being largely absent in finance, business and social science training, one should be able to see some similarity to the case of financial engineering training and related unintended practical outcomes. Economists understand well that modeling social dynamics is not a trivial exercise, both in terms of the theory and the applications. Behavioural economists can further adhere to the severe considerations involved when considering predictions, forecasts and expectations within social networks. When considering the design of processes or products that embed social interaction and can impact societal well-being, one must be aware of the related dynamics and potential limitations. Not all of these can be addressed by technology on its own or be embedded in a smart contract or be left to chance when customizing a process or service.

The development of technologies, such as the blockchain, is supposed to entail great potential to lead to more efficient outcomes, via bringing anonymity, trust in the underlying technology, transparency and several other desirable properties. However, for the technology and its applications to be developed in a way that enables efficient, welfare-enhancing, capability-enhancing and real economic and societal outcomes, the architects, engineers and developers of that technology would need to be trained via a modern integrated curriculum. That curriculum would need to be built on solid foundations, for instance, without mere rushing in following any short-term market trend. Furthermore, the recent history can not help emphasise enough that among the core skills of this curriculum should be critical thinking, business ethics, and understanding regulation and compliance. Such a skill portfolio would enable FinTech applications founded upon strong technical skills, alongside the understanding of societal dynamics. If such applications are to come to fruition, then one can feel safe that FinTech is a true opportunity for a much-needed positive disruption in practices, which can enhance financial capability and societal well-being.

Chapter 3: Financial Literacy and Attitudes to Cryptocurrencies

3.1 Introduction

The emergence of cryptocurrencies using both cryptography and blockchain technology in 2009 signalled a major turning point for the financial world. As of end October 2020, there are more than 5,000 cryptocurrencies in circulation, with an estimated market capitalisation close to USD400 billion. Both the number of cryptocurrencies and their market capitalisation have more than doubled in one year.

The supply of cryptocurrencies is inherently complex and typically limited. In the case of bitcoin, currency is only released into circulation when miners are rewarded for processing and verifying transactions and finding solutions to cryptographic puzzles of increasing difficulty. While the number of units circulating and maximum supply of cryptocurrencies such as bitcoin has been the subject of academic discussion, until recently the demand side of the market was much less well understood, and considered to be largely unpredictable (Baur, et al., 2018). The ability of cryptocurrencies to facilitate anonymous peer-to-peer transactions without the need to involve third parties has been flagged as a potential driver of demand. Intuitively, users interested in these characteristics are unlikely to reveal their motivation and preferences or provide information about the specifics of their engagement with cryptocurrencies. Nevertheless, in their recent seminal study, Foley, et al. (2019) estimate that around USD76 billion of illegal activity per year involves bitcoin transactions – accounting for some 46% of all bitcoin transactions.

Bitcoin prices famously rose to over 18,000 USD at the end of 2017, before plummeting again and continuing to fall throughout 2018 to a low of under 4,000 USD. Prices increased again to just under 13,000 USD in 2019 and have continued to fluctuate in 2020 with a large decline in March once again followed by a rally. This fluctuation in market price has led to demand from retail investors seeking super-normal returns, rather than an alternative currency. In an early study, Glaser, et al. (2014) reports '*strong indications that especially uninformed users approaching digital currencies are not* *primarily interested in an alternative transaction system but seek to participate in an alternative investment vehicle*'[3].

Rooney and Levy (2018) point out to the emergence of some 300 crypto funds, or funds that engage only in cryptocurrencies. These are actively managing some USD10 billion in assets. PwC (2020) reports that in the 1st quarter of 2020 there are around 150 active crypto hedge funds, two thirds of which (63%) were launched in 2018 or 2019. The remaining crypto funds are likely to be index funds, or 'trackers' that are invested in a basket of cryptocurrencies.

This study sheds further light on the demand for cryptocurrencies by examining the determinants of attitudes to cryptocurrencies using data from a new consumer survey covering 15 countries. I attempt to identify the characteristics of cryptocurrency users and prospective users, focusing particularly on their financial literacy in terms of their understanding of fundamental financial concepts. Since cryptocurrency users who are engaged in illegal activity and the managers of cryptofunds are less likely to respond to surveys, I aim to examine the characteristics of the general population of ordinary users. This population is understudied but widely served by FinTech providers through cryptocurrency exchanges, dedicated platforms, digital wallets and related Apps. I aim to assess whether financial literacy is a key determinant for the demand for cryptocurrencies. Are the more financially literate more or less likely to be aware of cryptocurrencies? Is financial literacy positively or negatively related to current cryptocurrency ownership? Does it affect the positive or negative disposition towards cryptocurrencies among prospective owners? Are factors such as digital literacy skills, age, preference for informal practices, and financial advice interacting with financial literacy in determining the demand for cryptocurrencies? Evidently, the investigation of the relationship between financial literacy and attitudes to cryptocurrencies is important for several reasons.

First, the FinTech era has introduced investors to a range of new financial markets and instruments, many of which are accessible via digital channels, without intermediation,

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[3] The authors examine trading data from a bitcoin exchange, transaction data from bitcoin blockchain, visitor statistics for the bitcoin Wikipedia article and dates of important bitcoin events.

advice and/or monitoring by an authorized body. Yet financial markets and instruments were already considered complex by most non-expert users (e.g. Remund, 2010; Van Rooij, *et al.*, 2011). In the novel territories of the FinTech era, the ability of even inexperienced investors to engage in informed financial decision making becomes paramount.

Second, cryptocurrencies have been characterized by extremely high volatility. One of the key tenets of the global financial literacy enhancement agenda involves increasing consumers' ability to understand and assess the financial risk involved in different choice options. IOSCO and OECD's (2019) *Core Competencies Framework on Financial Literacy for Investors* entails 7 key elements, all of which are highly relevant to cryptocurrency investors. Examples include: '*Explain the difference between investing and speculation*'; '*Identify and compare the features and risks of different asset classes';* '*Identify the cyber security risks of using online platforms for investing*'; '*Differentiate between an unrealized and realized gain/loss*'; '*Be aware that investors may not always make rational decisions due to biases*', and' '*Describe the main features of common investment scams and frauds*', *inter alia* (OECD, 2018: 4-5). One would expect the more financially literate to be less likely to engage in a highly volatile new instrument and in transactions driven by unrealistically high promised rewards or by sentiment and imitation.

Third, cryptocurrencies have spurred considerable debate among industry experts, academics, policymakers and regulators, and acquired 'sworn' enemies and 'zealot' followers. They have received rapturous appraisals by certain technology and investment gurus. They have attracted a large volume of new investors and speculators, and they are frequently the subject of discussion in the media. One could expect the financially literate to be affected more by networks, advisor and peers that encourage the transfer of knowledge rather than mere imitation (Haliassos, et al., 2020).

Fourth, the design and range of cryptocurrencies is relatively new and evolving. For example, new ideas entailing notions of 'stable coins', which possess features of both crypto and fiat money, have been put forward as the future of the market for cryptocurrencies. The proposal is for these to be pegged or linked to a major currency such as the dollar or the euro. One such instance is the inception of Libra by Facebook, which was aspired to go in circulation in 2020, but has also recently seen criticism by investors and regulators, including the US Congress, the Federal Reserve Board, and the Financial Stability Board. In particular, Randal K. Quarles, the chairman of the Financial Stability Board, warned the finance ministers and central-bank governors of the G20 in writing that stable coins are likely to become a source of threat to global financial markets (FSB, 2019). Regulators are concerned because of the limited insight and monitoring capacity on cryptocurrencies and the several likely, but poorly anticipated, risks entailed in such new instruments (Foley, et al., 2019).

Several central banks have also expressed interest in the potential establishment of a central bank digital currency (CBDC). Although not necessarily founded upon the same underlying technologies, or Decentralised Finance (DeFi) principles, as cryptocurrencies, CBDCs are seen a likely key ingredient of future international monetary systems. A speech by Christine Lagarde, President of the European Central Bank (ECB), at the Deutsche Bundesbank on 10th September 2020 is a prominent example, highlighting the potential of a digital Euro in facilitating international payment systems, strengthening monetary sovereignty and trust, along with the position in the dominance of global payments. However, President Lagarde also emphasized the risks that the establishment of a digital Euro would entail and suggested that people might not be aware of these risks.

If the current cryptocurrency market has been dominated by illegitimate users, a few sophisticated 'crypto fund' managers, many speculators, and many more unsophisticated and potentially less financially literate investors, then concerns about consumer detriment and sources of risk are entirely justified. This is particularly the case for newly established markets involving novel alternative instruments available to the wider, even global population. If a market is dominated by users interested in illegal affairs and by unsophisticated investors, then the future of that market is likely to be opaque. It can even endanger financial stability if cryptocurrencies attract increasing numbers of unsophisticated investors who finance their demand via borrowing. It can be a source of risk to the financial resilience of households if the related demand occurs as part of a non-diversified portfolio of investments, substituting limited savings or rainy-day funds.

Our main empirical question is whether the more financially literate are more likely to engage in the market for cryptocurrencies, in terms of owning and/or intending to own cryptocurrencies. I are also interested in the moderators underlying any such relationship, for example, if any effect of financial literacy can be explained by digital literacy, age, inclination to informal practices, financial advice, or the enhanced understanding of the financial risk involved in cryptocurrencies. With all the media attention and the likely peer pressure from acclaimed cryptocurrency investors, it is likely that more present-biased individuals and those with limited risk awareness or erroneous risk perceptions are prone to indulge in sentiment-driven decision making and peer pressure. It is of interest to examine whether those who are financially literate and present biased are more or less likely to consider investing in in cryptocurrencies.

Our study utilises data from the ING 2018 International Survey on Mobile Banking. The online survey questioned a representative sample of the general population aged 15+ in each of the 15 participant countries. Countries include the USA, Australia, the United Kingdom, several members of the European Union, along with countries in Eastern Europe and Central Asia (hereafter *ECA*). Apart from the usual demographics and use of mobile banking, the survey covered awareness of, and attitudes to cryptocurrencies, in terms of having heard of cryptocurrencies, current holdings, and future plans to own cryptocurrencies (ING, 2018). my empirical approach matches the data from this survey with data from the S&P 2014 Global Financial Literacy Survey (Klapper, Lusardi and von Oudheusden, 2015), based on country, gender, age and income groups. This exercise enables the generation of a financial literacy proxy, capturing the probability of knowing at least 3 of the 4 main financial literacy concepts, i.e. inflation, simple interest/numeracy, compound interest, and financial risk. my measure approximates this probability based on a score calculated as the average percentage of 3-out-of-4 correct answers for respondents of a given gender, age group (15-34, 35-54, ≥55) and income band (top 60%, bottom 40%) in each country. I also experiment with additional financial literacy proxies that standardise any country-level differences in financial literacy.

Cryptocurrencies are held by 9.3% of the respondents aged 18-65 in the 15 countries surveyed, and a further 14.1% intend to become cryptocurrency owners in the future. Some 42.4% of the sample neither own nor intend to own cryptocurrencies, whilst the remaining

34.1% have never heard of cryptocurrencies before. my figures for cryptocurrency ownership among 18-65 year-olds are 8.9% in the USA, 7.1% in Australia, 7.2% in the United Kingdom, and 9% in Germany. Similar proportions of ownership in these countries have been found in other studies. A survey by YouGov in the USA found that some 9% of respondents who had heard about cryptocurrencies had bought bitcoin whilst 5% had mined them (Yougov, 2018b; 2019). Jakubauskas (2018) reports rates of cryptocurrency ownership of 9% in the United Kingdom and 6% in Germany. The figures are also in line with the cryptocurrency benchmarking study by Rauchs, et al. (2018) and the reports by Yougov, (2018a) and the FCA (2019). my figures for ownership and intention to own are notably high among the ECA countries, i.e. Turkey, Romania, the Czech Republic, and Poland. A striking 17.7% of the sample in Turkey own some cryptocurrency, with an additional 24.4% not owning but intending to own in the future. Spain also exhibits high figures of current and prospective ownership, for instance, 10.5% and 18.9%, respectively. my results also show that males, younger adults, and the more educated are more likely to engage in the cryptocurrency market.

I estimate weighted multinomial probit models of attitudes to cryptocurrencies, in terms of four categories capturing current ownership, the intention to own in the future, no intention to own in the future, and having heard of cryptocurrencies. my financial literacy proxy is the independent variable of primary interest, but I also include a rich set of control variables for demographic characteristics, and PPP-deflated monthly income per capita. I also generate proxies for digital literacy, preference for cash as an indication of inclination to informal practices, and intertemporal preferences captured by the future-time reference of the respondent's language. Chen (2013) describes language as a powerful marker of intertemporal preferences, via a linguistically induced bias in time perception or a deeper driver of precision of beliefs about time. Strong inflectional FTR languages, like English, have been associated less future-oriented behaviour. Present-biased beliefs have been associated with engagement in more risky behaviours, e.g. lower saving rates and less healthy lifestyles, inter alia.

To my knowledge, my study is one of the first to examine the relationship between financial literacy and attitudes to cryptocurrencies on a global scale. Recently, in a contemporaneous study to ours, Fujiki (2020) finds a positive impact from financial literacy on cryptocurrency ownership in Japan. However, the author finds a larger negative impact from financial education, and controls for several other financial literacy proxies in the same specification. Hence, this contemporaneous finding seems unlikely to be robust and could be due to multicollinearity. Moreover, there are recent inquiries in different aspects of the demand for cryptocurrencies. Hasso, *et al.* (2019) examine brokerage accounts and show that men are more likely than women to engage in cryptocurrency trading, trade more frequently, and be more speculative. As a result, men realise lower returns. Bannier, et al. (2019) find that women know less about the characteristics of bitcoin than men. They suggest that actual and perceived financial literacy explains approximately 40 percent of the gender gap in bitcoin literacy. Lammer, et al. (2020) use data from an online German bank and examine the investment behaviour of individuals who invest in cryptocurrencies with structured retail products. They report that cryptocurrency investors are active traders, prone to investment biases, and hold risky portfolios.

Our estimates reveal that people who are more financially literate are less likely to own cryptocurrencies and more likely not to intend to own them in the future. As expected, they are more likely to have heard of cryptocurrencies before. The results are economically and statistically significant. An increase in the financial literacy score of one standard deviation (0.1470) from the average of 0.5133 decreases the predicted probability of cryptocurrency ownership by 39.6%, i.e. by 3.71 percentage points − from 9.41% to 5.7%. The same increase in the financial literacy score increases the probability of having no intention of holding cryptocurrencies in the future by 22.7% and it decreases the probability of claiming to never have heard of cryptocurrencies by 18.8%. The results are robust in models with interaction terms between financial literacy and country[4], as well as models with interaction terms between financial literacy, education, and income. The results are also robust in models using bootstrapping, unweighted models, and models using alternative financial literacy proxies which standardise any country-level differences in financial literacy. In addition, they are robust to the use of a multinomial probit model with selection, in which awareness of cryptocurrencies is the dependent variable in the first

[4] These models also indicate some country heterogeneity in cryptocurrency ownership, in terms of positive effects of the interaction terms between financial literacy and Germany, Luxembourg, the Netherlands, Australia, and the Czech Republic.

stage. Finally, they are robust to an instrumental variable model that caters to concerns regarding omitted variable bias.

I examine the external validity of my findings using data from the OECD 2019 Consumer Insights Survey on Cryptoassets which reports findings from a survey of 3,428 consumers and retail investors in Malaysia, the Philippines, and Vietnam (OECD, 2019). The online survey explored retail investors to collect data on consumers' attitudes, behaviours and experiences in relation to cryptocurrencies and initial coin offerings. Importantly, the questionnaire also included financial literacy questions. The level of cryptocurrency holding was higher than found in other markets: 36.8% of the investors currently own some cryptocurrency, 14.6% previously owned, 31.1% never held any cryptocurrency, and 17.5% have never heard of cryptocurrencies. my estimates suggest the more financially literate respondents in these three markets are 10.8% more likely to have never held cryptocurrencies. Instrumental-variable estimates also confirm financial literacy's large negative impact on the probability of current ownership and a large positive impact on the probability of not having held cryptocurrencies.

Using the ING International Survey, I investigate the specifics of the negative relationship between financial literacy and cryptocurrency ownership, in terms of the candidate variables that can moderate this relationship. I show that digital literacy[5] exerts a large, positive impact on current cryptocurrency ownership and on the intention to become an owner in the future. However, in models with interaction terms between financial literacy and digital literacy, the effect of financial literacy remains significant and is of similar magnitude to my baseline estimates. Moreover, I examine whether preference for cash can conceptually serve as a proxy for favourable attitudes to informal practices and whether it might moderate the effect of financial literacy on cryptocurrency ownership. I find that a higher preference for cash is significantly positively related to cryptocurrency

[5] The importance of digital competence was recognised by the European Commission (2006; 2014) in its recommendation on key competences for lifelong learning when it identified digital competence as one of eight key competencies essential for all individuals in a knowledge-based society. The American Library Association (2016) offers this definition: "*Digital literacy is the ability to use information and communication technologies to find, evaluate, create, and communicate information, requiring both cognitive and technical skills*". my digital literacy is computed as the number of items owned among the following: (1) Smartphone; (2) Tablet; (3) Smart TV; (4) Mobile phone (but not a smartphone); (5) Wearable device (such as an Apple Watch).

ownership and awareness, and negatively related to the intention not to own in the future. The positive relationship between preference for cash and cryptocurrency ownership can be explained by their comparably higher levels of anonymity or privacy they offer to users (Darbha and Arora, 2020). Anonymity in choice of transacting is preferred informal markets. Although there is a positive effect of the interaction term between financial literacy and preference for cash on the probability of intending to own cryptocurrency in the future, the main effects of financial literacy remain robust in economic and statistical terms. I also find that cryptocurrencies are more popular among individuals under the age of 45, but age is not the primary moderator of the established relationships between financial literacy and attitudes to cryptocurrencies. This is also the case for the likely moderating role of financial advice regarding cryptocurrencies[6]. The effect of financial literacy is robust in models with interaction terms between financial literacy and financial advice. There is a negative effect on cryptocurrency ownership by the interaction term between financial literacy and advice from the internet and specialist websites, signalling that the more financially literate might be better able to seek financial information online.

The perception of the relative risk of cryptocurrencies and alternative assets is employed to explain the established relationship between financial literacy and attitudes to cryptocurrencies. I estimate models with interaction terms between financial literacy and such risk perceptions and I find significant effects of these interaction terms. Moreover, the effect of the financial literacy variable diminishes in terms of both magnitude and significance in these models. The robustness of my proposed moderator is confirmed by the greater negative impact on cryptocurrency ownership and the intention to own in the future by the financial risk constituent of the financial literacy measure. Finally, I estimate models including an interaction term between financial literacy and intertemporal preferences, for instance, the future-time reference of the respondent's language (hereafter inflectional FTR). I find a large negative effect of these interaction terms and interpret this as signalling that greater financial literacy skills, namely a more informed perception of

[6] Cryptocurrency owners and prospective owners are more likely to have a source of financial advice. Starting from the effect of the highest magnitude. The following sources of advice exert positive significant impacts on cryptocurrency ownership: online programmes or algorithms for tailored advice, the internet and specialist websites, friends and relatives, and lastly, by an independent financial or bank advisor.

financial risk, might be conducive to more prudent financial decision making by the present biased.

Our study presents evidence suggesting that individuals with higher financial literacy are less likely to hold cryptocurrencies in their portfolio, despite displaying higher awareness about them. This is consistent with the observation that cryptocurrencies have their own intrinsic complexities, any reflects a more informed perception of financial risk. my results have implications for the efficiency of the cryptocurrency market. If the cryptocurrency market is dominated by users engaging in illegal transactions and unsophisticated users, as the less financially literate in my study, then the policy makers in central banks are right to be concerned about potential threats to global financial stability from the cryptocurrency markets. They should also be concerned about the financial well-being of the users of cryptocurrencies. Considering Facebook's proposal to develop stable coins, pegged to a major currency and made available to its 2.4 billion users, there should be concerns regarding the financial well-being and overall welfare of this major global audience. In addition, my results highlight several implications specific to the ways in which cryptocurrency investments are financed. Baur, et al. (2018) posit that if bitcoin investments are leveraged, a significant fall in its value could lead to margin calls and then also affect other assets. Liu and Tsyvinski (2018) find that certain industries have significant exposures to bitcoin returns, both positive (Consumer Goods and Healthcare) and negative (Fabricated Products and Metal Mining). Although the authors find no exposure of the Finance, Retail and Wholesale industries, a radical proposal such as Facebook's stable coin in a universe of unsophisticated traders and debt-financed usage might indeed entail severe implications for macroeconomic and international financial stability.

Our study supports the view that more financially literate consumers may also help to contribute to better functioning financial markets (Hilgert et al., 2003). Liu and Tsyvinski (2018) also find that high investor attention predicts high future returns over short horizons for bitcoin and Ripple and medium-term horizons for Ethereum. The authors document herding effects by showing that high negative investor attention negatively predicts future bitcoin returns. Any future cryptocurrency proposal could therefore benefit from parallel programmes that can increase both financial literacy and transparency in the cryptocurrency market. This is in line with a similar suggestion by Georgarakos and Pasini (2011) for promoting higher national equity ownership. Indeed, the presentation format of financial information has been shown to affect more individuals with low skills in financial literacy (Hastings and Tejeda-Ashton, 2008; Hastings and Mitchell, 2018). In view of the evidence by Haliassos, et al. (2020) regarding exogenous peer effects and a social-multiplier effect on financial knowledge, a network dominated by largely unsophisticated users is more likely to overreact or underreact to different types of information, in the absence of fundamentals.

The remainder of this study is organised as follows. *Section two* reviews the market for cryptocurrencies and makes the conceptual link between financial literacy and the demand for cryptocurrencies. *Section three* presents the data, the summary statistics of the key variables and my empirical strategy. Then, *Section four* presents the results of the estimates for the role of financial literacy on attitudes to cryptocurrencies, along with the relevant robustness and external validity exercises. *Section five* presents the inquiry regarding the main moderators that are likely to explain the effect of financial literacy on the demand for cryptocurrencies. Finally, *Section six* concludes and discusses the relevant implications of the findings.

3. 2. Background and literature

3.2.1 The market for cryptocurrencies

Figure 3.1 presents the eighteen cryptocurrencies with the highest market capitalisation for the period 2016-2019, namely Bitcoin, Bitcoin Cash, Bitcoin SV, ChainLink, Dai, Dash, EOS, Ethereum, Ethereum Classic, IOTA, Litecoin, Monero, NEM, NEO, Ripple, Stellar, Tether and Tezos. Their market capitalisation at the end of 2019 is around USD300 billion. Bitcoin alone represents around half of this market capitalisation, as can be seen at the top panel of Figure 3.1. Overall market capitalisation picked in late 2017, with that of bitcoin exceeding USD300 billion. However, the following years saw significant fluctuations. Following the sharp drop in its price in early 2018 and continuing decline throughout most of the year, bitcoin's market capitalisation fell to USD60 billion in February 2019 and increased once more to USD210 billion by July 2019. At much lower volumes, the other cryptocurrencies, and most notably Ethereum, displayed similar patterns in terms of the timing of changes in their market capitalisation up to December 2019. The bottom panel of Figure 3.1 contrasts the top figure with figures on the market capitalisation of the largest twelve S&P100 companies. The current market capitalisation of the entire cryptocurrency market is just close to that of each of the equities in the lower half of the top 12. Hence, the size of the cryptocurrency market is objectively small, but not negligible and with likely future growth potential.

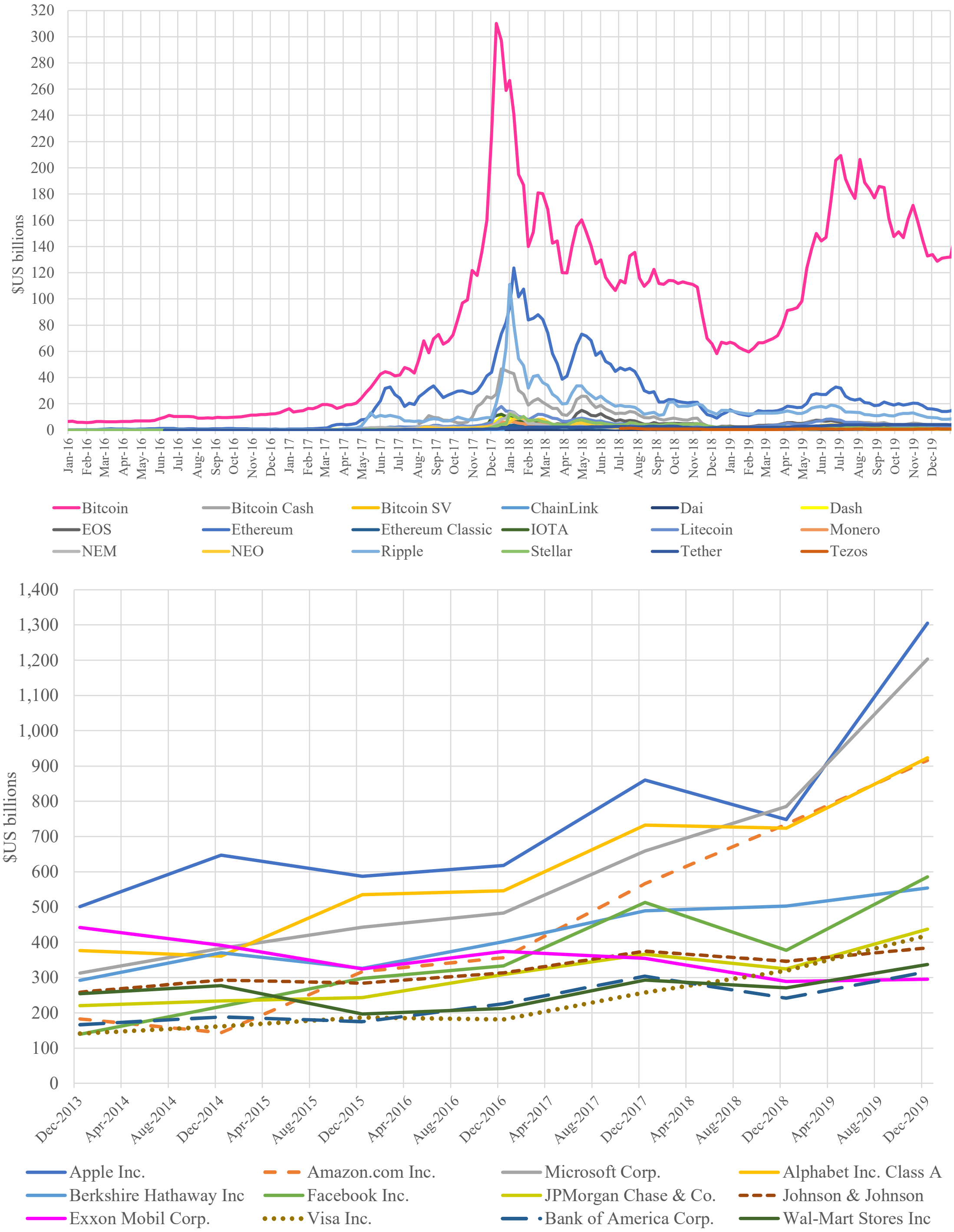

Figure 3.1

Market capitalisation among cryptocurrencies and the largest S&P companies

This figure presents the ten cryptocurrencies with the highest market capitalisation for the period 2016-2019, namely Bitcoin, Bitcoin Cash, Bitcoin SV, ChainLink, Dai, Dash, EOS, Ethereum, Ethereum Classic, IOTA, Litecoin, Monero, NEM, NEO, Ripple, Stellar, Tether and Tezos. The data on market capitalisation among cryptocurrencies is from: https://www.cryptocurrencychart.com/top/25. The data on the largest 12 S&P100 companies is from Bloomberg and http://siblisresearch.com/data/market-caps-sp-100-us/

Whilst the universe of cryptocurrencies is not homogenous, they share common features in terms of the use of both cryptography and blockchain technology, their facilitation by technology over the internet and the likely decentralisation within a network of users. Some cryptocurrencies, such as Ripple and NEO, function more as payment systems than others due to their more effective operation structure in confirming transactions (European Parliament, 2018).

Focusing on one of the first cryptocurrencies, bitcoin, can help us to better understand the market. Bitcoin was designed for irreversible online transactions (Nakamoto, 2008). The cryptocurrency's integrated payment transfer mechanism can be thought to function as a self-standing network that does not require intermediaries. However, in reality it is not widely used as a payment transfer mechanism. A very limited amount of goods and services are denominated in bitcoin and its fractions, i.e. '*Satoshis'*, and those services include the transaction fees on the bitcoin blockchain. Bjerg (2016) posits that bitcoin is like '*commodity money without gold, fiat money without a state, and credit money without debt*', and Yermack (2015) suggests that bitcoin serves more as a speculative investment than as a currency. The prevalence of massive speculative investing was also made evident during the rapid increase in cryptocurrency prices, especially in the price of bitcoin in late 2017 followed by an equally rapid decline in early 2018.

The supply of bitcoin is predetermined to be restricted to 21 million bitcoin units (Nakamoto, 2008). Bitcoin miners today typically use heavy duty computers requiring significant amounts of electricity to mine, process or verify transactions which are then incorporated into new blocks on the bitcoin blockchain. A new 1-megabyte block containing on average two thousand transactions is mined every 10 minutes, for which the successful miner receives 6.25 bitcoins per block (decreasing by design from 12.5 bitcoins prior to May 2020). In total, up to 1,800 new bitcoins are produced each day. Due to the increase of specialist mining rigs on the bitcoin network, and the increased complexity of the puzzle to be solved, the chances of a normal user being able to mine blocks has been reduced in the recent past. As a result, the average cryptocurrency user is more likely to purchase cryptocurrencies through an exchange or invest in an initial coin offering (ICO)[7] than acquire them from mining.

By design, the bitcoin blockchain system does not incorporate future cashflows or interest, apart from the compensation to miners for verifying transactions. The lack of attention to fundamentals can motivate investors to contribute to speculative price increases, such as that witnessed in the Californian real estate market in the late 1980s (Shiller, 1990). Exacerbated by the limited supply feature and the related scarcity element, limited knowledge and/or attention may have contributed to the sudden increase in the price of bitcoin during the period between the late 2017 and early 2018.

Figure 3.2 presents the price development of bitcoin for the period between 2016-2019, compared to certain asset classes, namely gold, real estate, sovereign bonds, equities, and cash. The price of bitcoin reached that of gold in March 2017 for the first time and then the rally began, with the price of bitcoin reaching USD19,000 in December 2017, with that of gold remaining close to USD1,250 per ounce. The bottom panel of Figure 3.2 shows that the remaining asset classes exhibit far more stable prices than that of bitcoin. The sole exception are equities, with the proxy of the S&P Global 1200 total return index increasing from USD1,800 in January 2016 to USD2,500 in February 2018, then decreasing to USD2,000 by January 2019, and risking again to USD2,600 by December 2019.

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[7] Initial coin offerings (ICOs) are a new method of raising capital for early-stage ventures. In an ICO, a blockchain-based issuer sells cryptographically secured digital assets, usually called tokens. The ICO market raised over USD31 billion between January 2016 and August 2019, and at least 20 individual ICOs to date have taken in more than USD100 million (Howell, et al., 2020).

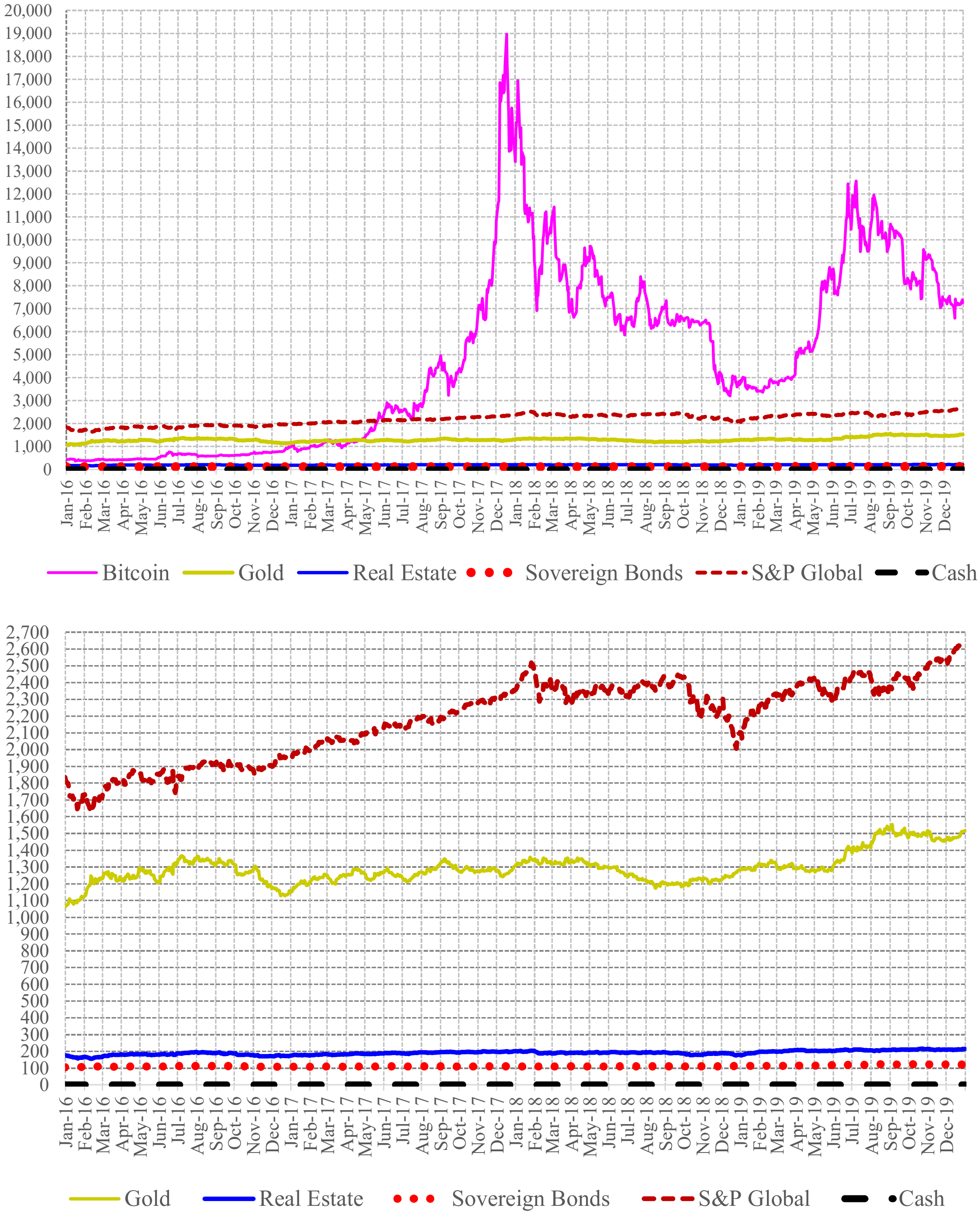

Figure 3.2
The price development of bitcoin and other asset classes between 2016-2019 (USD)

This figure presents the daily price development of bitcoin for the period between 2016-2019, compared to other asset classes, namely gold, real estate, sovereign bonds, equities, and cash. The data is from Bloomberg for the period 1.1.2016 – 31.12.2019. The price of the US T-Bill is used as a cash proxy. The Bloomberg Barclays GDP Core Developed Govt AA- or Above TR Hedged USD is used for sovereign bonds. The MSCI ACWI REAL ESTATE USD price index is used for real estate. The SP GLOBAL 1200 total return index is used for equities. The GOLD SPOT XAU in USD is used for gold. Bitcoin’s daily price in USD stems from Coindesk.

In standard financial instruments, scalability can make the services cheaper. In contrast, it seems that the greater popularity of bitcoin made the transactions on the blockchain more expensive. This has largely been seen as a difficulty of bitcoin network's ability to scale up and function as a payment system. However, its scarcity and limited scalability have meant that it is perceived more as a store of value, which can serve as a substitute to fiat money in situations of crisis or in regions of low financial inclusion, high currency volatility and/or low trust in financial institutions[8]. Nevertheless, when cryptocurrencies were compared to the currencies of the least developed countries between 2014 and 2017, the former were shown to exhibit more volatility (Kasper, 2017). Polasik, et al. (2015) discuss how the demand for bitcoin is higher in low-income countries, with large informal sectors and imprudent monetary policies. Bitcoin volatility was also found to be related to global economic and financial events (Conrad, et al., 2018). The top panel of *Figure 3.3* presents daily one-month running annualized volatilities for bitcoin and selected asset classes, namely gold, real estate, sovereign bonds, equities, and cash. It is evident that the volatility of bitcoin is several times that of stocks, gold, real estate, and bonds[9]. The bottom panel of the figure presents the corresponding volatilities in comparison to some international currencies, for instance, those of the countries in my study, namely the Polish Zloty, the Romanian Leu, the Turkish Lira, the Euro, the Australian dollar, the British pound, the US dollar, the Czech Koruna, the Philippines Peso, the Malaysian Ringgit and the Vietnamese Dong. It is only the Turkish Lira that has exhibited comparable volatility to bitcoin in the period after August 2018. Other countries exhibiting high volatility involve the Polish Zloty, the Romanian Leu, the Philippines Peso,

8 The demand for bitcoin seems to have surged during events such as the banking crisis of Cyprus in 2013 (Forbes, 2013) and the political unrest in Zimbabwe in 2017 (Telegraph, 2013). Moreover, following 2014, hyperinflation in Venezuela and the initiation of their own Petro cryptocurrency also increased the demand of bitcoin (Time, 2018). Furthermore, anecdotal evidence suggests cryptocurrency usage among refugees is high, providing transport security and facilitating remittances. The public dialogue has seen arguments emphasizing on the future potential of the blockchain technology facilitating functions among refugee communities, including financial inclusion and remittances (Flore, 2018; Forbes, 2019).

9 The *Appendix 1 Table A1* calculates the standard investment risk and return characteristics of bitcoin, in terms of the Sharpe and Sortino ratios. Bitcoin's volatility nearing 90% is compensated by higher returns during the 3-year period 2016-2019. However, in 2018, this high volatility corresponds to very large negative returns, which are much higher compared to the remaining asset classes. Bitcoin entails the largest negative Sortino ratio for the year 2018, compared to real estate and the remaining asset categories.

and the Euro after February 2019. However, the volatility of bitcoin is many times higher than that of all currencies.

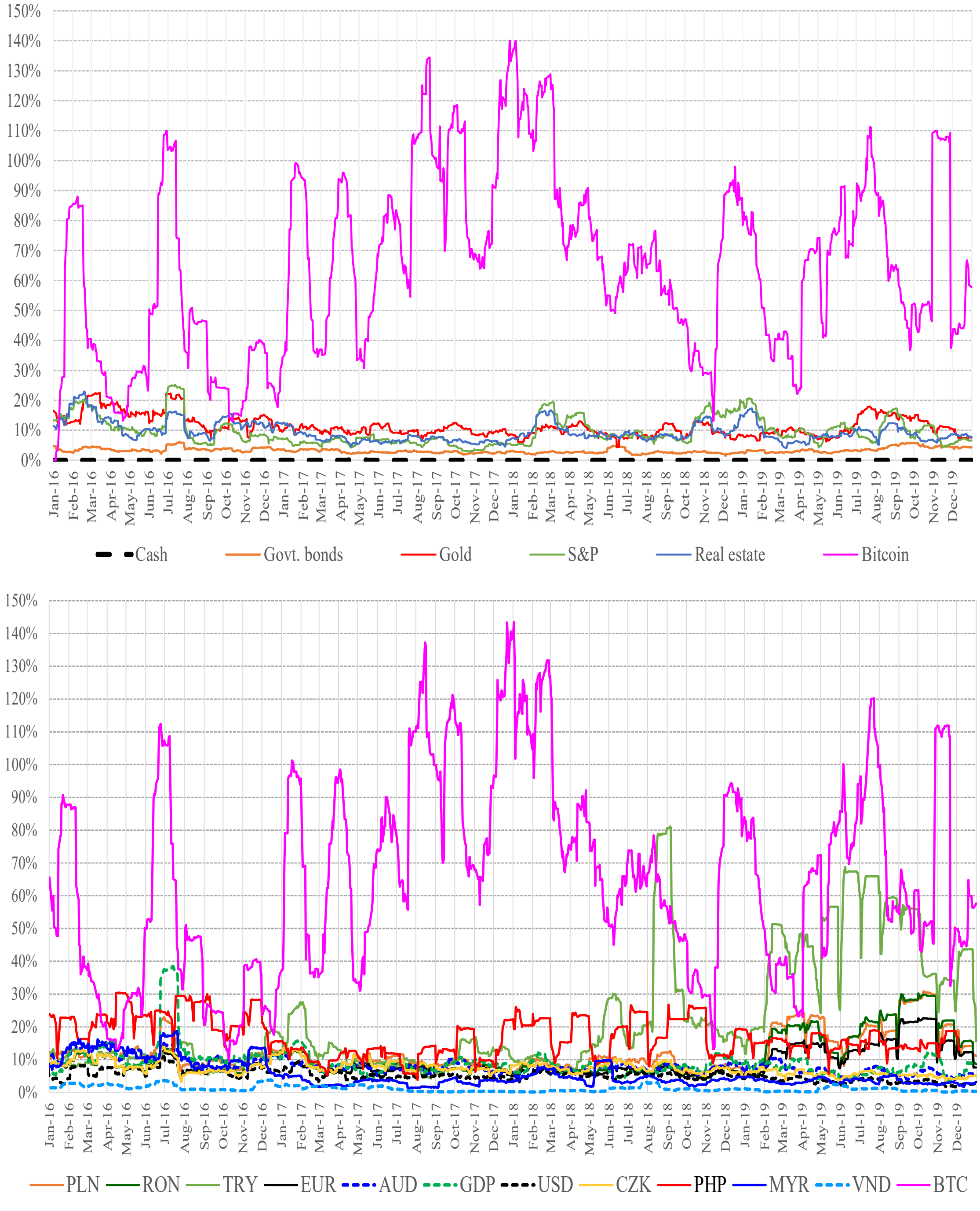

Figure 3.3

Daily one-month running annualised volatilities of bitcoin and international currencies

The top panel of this figure presents daily one-month running annualized volatilities for bitcoin and selected asset classes, namely gold, real estate, sovereign bonds, equities, and cash. The data is from Bloomberg for the period 1.1.2016 – 31.12.2019, and the proxies used are identical to those in Figure 2. The bottom part of the figure presents daily one-month running annualized volatilities for bitcoin and currencies of the countries in the ING International Survey on Mobile Banking and the OECD Consumer Insights Survey on Cryptoassets, namely the Polish Zloty, the Romanian Leu, the Turkish Lira, the Euro, the Australian dollar, the British pound, the US dollar, the Czech Koruna, the Philippines Peso, the Malaysian Ringgit and the Vietnamese Dong.

While the complex information on the supply side of cryptocurrencies is available to current and prospective users, e.g. the production, mining, technology, circulating and maximum supply, much less is known regarding the composition of the demand side. Such information is essential for price determination (Ciaian et al., 2015)[10].

In addition to the procurement of cryptocurrencies by miners, there appear to be three other dominant groups that seek to acquire them: illegal traders, ordinary consumers and large 'crypto funds'. Foley, et al. (2019), for example, estimate that some 46% of bitcoin transactions are related to illegal activity. Glaser, et al. (2014) assert that uninformed users are attracted to digital currencies as an alternative investment vehicle, rather than as an alternative transaction system, and the consensus seems to be that cryptocurrencies are perceived by the general public as assets rather than currencies (e.g. European Union, 2018)[11]. Finally, Rooney and Levy (2018) point to the emergence of some 300 'crypto funds', which manage some USD10 billion in assets. At least 150 of these are active crypto hedge funds (PwC, 2020).

Traditionally, assets are valued for their future revenue stream or the intrinsic utility that commodities entail. Financial instruments are considered to hold no intrinsic utility value and are essentially a claim on borrower's future income or assets. Cryptocurrencies may be thought to hold a utility through their own decentralized and self-governing systems that can provide a medium of exchange and a store of value, but their lack of traditional

[10] Böhme et al. (2015), Dwyer (2015) and Yermack (2015) present early introductions to the economics of bitcoin.

[11] Analyzing the functions of money, Jevons (1875) concluded that money allows utilities such as a medium of exchange, a measure of value, a store of value and a standard of deferred payment. Intuitively, money facilitates the exchange of goods and services through its sought characteristics for 'portability', 'indestructibility', 'homogeneity', 'divisibility', 'stability of value' and 'cognizability'. Shiller (2018) discusses the difficulty of applying technological advancements to substitute money citing the proposal to the Econometric Society during the years of the Great Depression (i.e. in 1932), by John Pease Norton, a former student of Irvin Fisher, for a dollar backed not by gold but by electricity. Despite the attention the proposal received in the years of deflation and lack of liquidity, it lacked a good reasoning for choosing electricity over other commodities to back the dollar.

financial fundamentals makes their value complex to calculate[12]. To complicate things further, whilst cryptocurrencies are largely designed to be decentralized, exchanges may have a certain influence on the volume of transactions and the resulting price, which is indicative of a certain tendency for centralisation of market power (e.g. Brandvold, et al., 2015).

As the demand for cryptocurrencies is unpredictable, it is difficult to forecast their future value and usage (Baur, et al., 2018). For instance, Garcia, et al. (2014), suggested a low bound to a fundamental price for bitcoin by considering the cost of electricity, user sentiment, social interaction, and adoption reinforcement. Indeed, Kristoufek (2013) posited that a crucial driver of bitcoin's price is mere sentiment-driven speculation, as sentiment is a key driver of most retail-investor phenomena (Barber and Odean, 2008). Liu and Tsyvinski (2018) find that there is a strong time-series momentum effect in cryptocurrency markets, with returns being predicted by factors that are specific to cryptocurrency markets. Importantly, proxies for investor attention strongly forecast cryptocurrency returns. Bianchi and Dickerson (2019) point out that the relation between volume, current and future returns depends on the relative significance of hedging versus speculative trade, as well as on the aggregate balance of informed vs. uninformed traders. The authors also highlight the presence of highly heterogeneous market participants, e.g. miners, individual traders, and large-scale investors.

3.2.2 Could financial literacy be relevant to the demand for cryptocurrencies?

Individuals' asset allocations are often characterized by certain common errors: low stock market participation, under-diversification, poor trading performance, and investment in actively managed and costly mutual funds (Beshears, et al., 2018). It is obvious that investment in the cryptocurrency market can be linked to the latter three errors, and it is not yet clear if the figures for cryptocurrency-market participation are similar to these for

[12] For instance, Brainard et al. (1990) view fundamental-based returns of equities as the firm's cash flow after tax minus depreciation, divided by the net replacement cost of assets. During the early 2000's, the newly-founded technological companies had limited cashflows and faced several valuation challenges. The observed increases in their equity prices were largely fueled by sentiment-driven investing by retail investors (Baker and Wurgler, 2007).

stock market participation[13]. However, there are potential inferences that can be made for the market for cryptocurrencies from the literature on stock market participation. For instance, individuals expecting higher stock market returns are more likely to participate in stock markets (Hurd, et al., 2011; Kezdi and Willis, 2011), while those who believe that other market participants might cheat them out of their investment will perceive lower expected returns and be less willing to participate (Guiso, et al. 2008). Greenwood and Nagel (2009) conclude that less experienced and younger investors are more likely to invest in over-priced assets due to lack of previous investing experience. Mistakes in investing are likely to take place when a new financial instrument is introduced (Campbell, 2006)[14].

Recent literature has linked financial literacy with avoiding financial mistakes and engaging in prudent financial behavior, e.g. formal vs. informal financial market participation (Klapper, et al., 2013), stock market participation (van Rooij et al., 2011; Almenberg et al., 2011)[15] and the frequency of stock trading (Graham, et al., 2009), negotiation of debt terms and repayment patterns (Moore, 2003; Campbell, 2006; Lusardi and Tufano, 2009a; b), levels of debt and default (Stango and Zinman, 2009; Gerardi et al. 2010), retirement planning (Klapper and Panos, 2011; Lusardi and Mitchell, 2011a; b; c), and banking of the unbanked population in developing countries (Cole, et al., 2011). The analysis in Lusardi, et al. (2017) indicates that financial literacy acquired early in life and shaping financial decisions around the lifecycle, can explain some 35-40% of retirement wealth inequality in the USA. Part of this could possibly be attributed to the improved ability by individuals to hold and trade stocks and effectively manage portfolios involving risky assets through diversification (e.g Calvet et al., 2007; Christiansen, et al., 2008; von Gaudecker, 2015, Bianchi, 2018)[16]. The ability of individuals to assess financial risk and

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[13] Guiso and Sodini (2013) find that only half of US households participate in the stock market. In several European countries, e.g. Greece, Italy, Spain, and Austria, the participation rates are below 10%.

[14] For instance, during the dot.com bubble in the late 1990s, higher participation rates were seen among the inexperienced younger investors (Greenwood and Nagel, 2009). These newly IPO'ed technology stocks were difficult to be valued, due to non-existent revenues and opaque growth characteristics. Due to the lack of fundamentals, the prices were seen as driven by sentiment-induced trading by the majority of the retail investors.

[15] van Rooij et al. (2011) report a certain lack of understand among retail investors about the differences between equities and bond investments, and a greater propensity to invest in the stock market. Christelis et al. (2010) also propose that higher cognitive abilities are positively related to direct stock ownership.

[16] Indeed, greater financial illiteracy has been linked to portfolio under-diversification. In von Gaudecker (2015), nearly all households that score high on financial literacy or rely on professionals or private

make optimal financial decisions has significant implications for portfolio allocation, wealth accumulation (Behrman, et al., 2012), and – ultimately – financial well-being.

Could the market for cryptocurrencies attract individuals with low financial literacy? Should I expect the financially literate to be in favour or against ownership and prospective ownership of cryptocurrencies, such as bitcoin? The literature has already pointed out that the market can attract sophisticated traders in a form of 'illegal traders' or 'crypto funds'. Wang (1994) and Llorente et al. (2002) show that trades based on private information are mimicked by uninformed investors, resulting in return continuations following high volume periods, and price reversals following low-volume periods. If the more financially literate are more likely to participate in stock markets, have a more diversified asset portfolio and obtain higher asset returns, it is likely that they will also be more likely to engage in the cryptocurrency market. On the other hand, if the more financially literate are better positioned to assess financial risk, minimise financial decisions based on imitation and sentiment, and/or overcome or avoid the formation of mistaken beliefs and expectation of constantly high returns, then they might be less likely to engage in the market for cryptocurrencies. Indeed, low financial literacy has been associated with mistaken perceptions and beliefs about financial products and less willingness to accept financial advice (Anderson, et al., 2017)[17].

Hence, my primary research question is whether the more financially literate are more or less likely to own and/or to intend to own cryptocurrencies, than those with low levels of financial literacy. my secondary set of research questions involves the moderating factors in any relationship between financial literacy and cryptocurrency ownership. As I previously highlighted, these may include digital literacy, age, preference for cash and

contacts for advice achieve reasonable investment outcomes, and these group differences stem from the top of the loss distribution. Bianchi (2018) finds that more financially literate households hold riskier positions when expected returns are higher. They are more likely to actively rebalance their portfolios and to do so in a way that holds their risk exposure relatively constant over time, and they are more likely to buy assets that provide higher returns than the assets that they sell. In addition, Choi, et al. (2010) and Duarte and Hastings (2012) relate financial literacy with choosing a low-fee investment portfolio.

[17] Collins (2012) shows that financial literacy and financial advice are complementary rather than substitute. For instance, if the more financially literate have access to better financial information and financial advisors (Calcagno and Monticone, 2015; Stolper, 2018), then it could be the case that optimal financial advice drives the relationship between financial literacy and attitudes to cryptocurrencies, rather than knowledge per se.

informal practices, and financial advice. Intuitively, they could involve a more 'enlightened' understanding of the risk and reward prospects of cryptocurrencies. Indeed, evidence from financial literacy surveys around the world indicates that questions relating to financial risk are the most difficult for respondents to contextualise and respond correctly (Lusardi and Mitchell, 2014; Montagnoli, et al., 2020).

3.3. Data and Empirical Strategy

3.3.1 The ING 2018 International Survey on Mobile Banking

I utilise the ING 2018 International Survey on Mobile Banking[18]. The survey was conducted between 26th March and 6th April 2018 by Ipsos International[19]. The data collection took place in 15 countries, namely the United States, Australia, the United Kingdom, Austria, Belgium, France, Germany, Italy, Luxembourg, the Netherlands, Spain, the Czech Republic, Poland, Romania, and Turkey. Around 1,000 people were surveyed in each country, with the sole exception of Luxembourg, in which 500 individuals were interviewed. The sampling is representative of gender ratios and the age distribution, selecting from pools of possible respondents furnished by panel providers in each country. In addition, sampling weights are provided by the data collectors to render the data representative of the population by country. The final sample comprises of 14,828 adult respondents who were interviewed online. In my analysis, I drop the very few respondents with no educational qualification, i.e. 90 observations, and another 1,471 respondents who were aged more than 65 at the time of the interview. my resulting sample comprises of 13,267 individuals, aged 18-65. 48.6% are male, with an average age of 42 years. 49.7% are married, 48% are employed full-time, 12.3% are employed part-time, and 6.4% are self-employed. 22.2% have a university degree, and 14.2% have a postgraduate university degree. The average household income per capita (PPP-divided) is €1,078.3 per month and there are missing income observations for 10.6% of the sample.

The ING International Survey inquired about how cryptocurrencies, such as bitcoin, are perceived across the European Union, ECA, the UK, the USA and Australia. The surveyors defined cryptocurrency as '*a type of digital currency not created or secured by the government but by a network of individuals*'. The question that enables the depiction of attitudes to cryptocurrencies was the following: "*Have you ever heard of cryptocurrency? If so, do you own any?*". The response categories involved: (a) I have heard of cryptocurrency; (b) I own some cryptocurrency; (c) I expect to own

[18] The data and documentation are available upon request to ING.

[19] The survey took place shortly after a period of rapid increase and then a sharp decrease in the prices of several cryptocurrencies, most notably bitcoin, during late 2017 and early 2018.

cryptocurrency in the future. The grid options for each of the three items involved: (I) Yes, and (II) No. As a result, the wording of the question enables the generation of a categorical variable for attitudes to cryptocurrencies entailing four categories, namely: (1) Own cryptocurrencies at present; (2) Don't own and expect to own in the future; (3) Don't own and don't expect to own in the future, and; (4) Have not heard of cryptocurrencies before.

3.3.2 Attitudes to cryptocurrencies

Figure 3,4 presents the frequencies of responses to the main question regarding attitudes to cryptocurrencies, overall and for each of the 15 countries in the sample from the ING Mobile Banking Survey. Weighted averages are shown for the four categories of responses, i.e. owning cryptocurrencies, not owning but intending to own, not owning and not intending to own, and not having heard of cryptocurrencies. The bars indicate that 9.3% of individuals in the sample own some cryptocurrency. 14.1% do not own but intend to own in the future. Some 42.5% of the sample do not own and do not intend to own cryptocurrency. The remaining 34.1% have never heard of cryptocurrency before. The figure of ownership is 8.9% in the USA and 7.1% in Australia. In the USA 12.1% of the sample intends to own cryptocurrencies and 37% does not intend to own in the future. The corresponding figures for Australia are 10.1% and 53.4%, respectively. 42% of the US sample has never heard of cryptocurrencies, with the figure for Australia being lower, i.e. 29.4%.

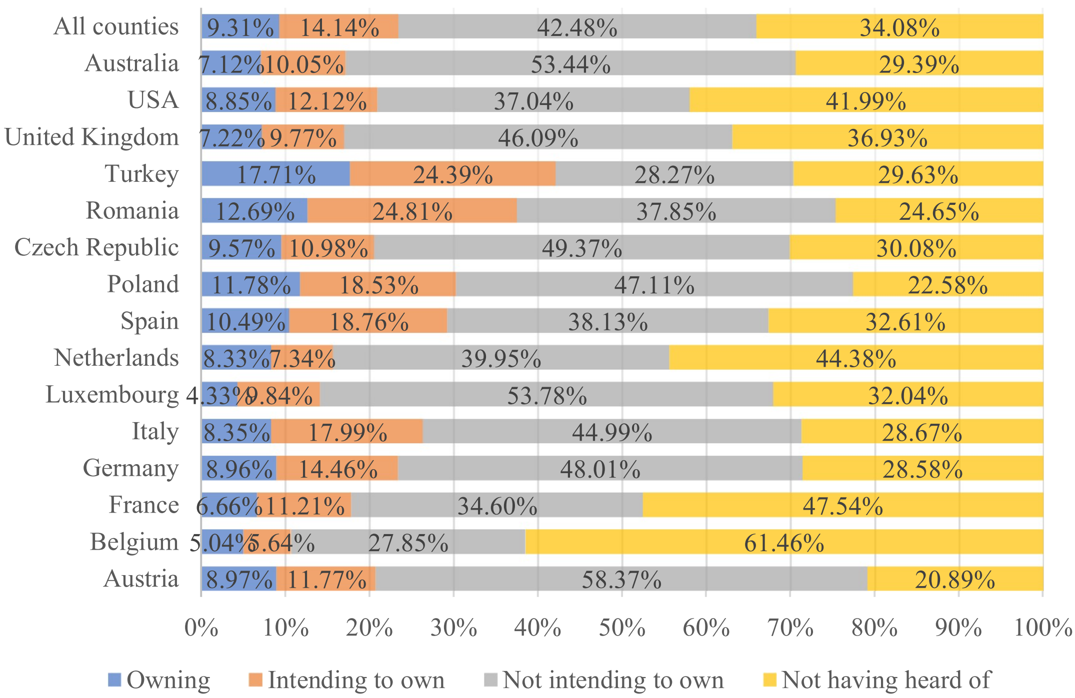

Figure 3.4
Attitudes to Cryptocurrencies (ING International Survey on Mobile Banking, 2018)

This figure presents the frequencies of responses to my main question regarding attitudes to cryptocurrencies, overall and by country. Weighted frequencies are shown for the four categories of responses, i.e. owning cryptocurrencies, not owning but intending to own, not owning and not intending to own, and not having heard of cryptocurrencies.

The figures for ownership and intention to own are notably high among the *ECA* countries in my sample, i.e. Turkey, Romania, the Czech Republic, and Poland. The latter three countries are among the newest member countries in the European Union. A striking 17.7% if the sample in Turkey own some cryptocurrency, with an additional 24.4% not owning but intending to own. The figures for not intending to own and not having heard of cryptocurrency in Turkey are 28.3% and 29.6%, respectively. The high figures of ownership and intention to own cryptocurrency can be related to uncertainty stemming from the recent high volatility in the Turkish lira, which is also evident in the second panel of Figure 3. In Romania, some 12.7% of respondents own cryptocurrencies, with another 24.8% intending to own in the future. 37.9% do not intend to own and a remaining 24.7% have never heard of cryptocurrencies. In the Czech Republic, the figures for the four categories are 9.6%, 11%, 49.4%, and 30.1%, respectively. In Poland, 11.8% of the sample own some cryptocurrency, with an additional 18.5% intending to own in the future. Some 47.1% do not intend to own, and a rather small figure of 22.6% have never heard of cryptocurrencies.

In the United Kingdom, 7.2% of the sample owns cryptocurrencies, with an additional 9.8% intending to own in the future. The corresponding Australian figures are similar, i.e. 7.1% and 10.1%). 46.1% of the UK sample does not intend to own cryptocurrencies in the future, and some 36.9% have never heard about them. Among the old member countries of the European Union, the figures for ownership (and intention to own) are: a rather high 10.5% (18.8%) in Spain, 8.3% (7.3%) in the Netherlands, 4.3% (9.8%) in Luxembourg, 8.4% (18%) in Italy, 9% (14.5% in Germany), 6.7% (11.2%) in France, 5% (5.6%) in Belgium, and 9% (11.8%) in Austria. 38.1% of the Spanish respondents have heard of cryptocurrencies but do not intend to own them in the future. The figures for negative inclination towards future ownership of cryptocurrencies in the remaining old EU countries are: 40% in the Netherlands, 53.8% in Luxembourg, 44.5% in Italy, 48% in Germany, 34.6% in France, 27.9% in Belgium, and 58.4% in Austria. Finally, the fraction of individuals who have never heard of cryptocurrencies are 32.6% in Spain, 44.4% in the Netherlands, 32% in Luxembourg, 28.7% in Italy, 28.6% in Germany, a high 47.5% in France, a striking 61.5% in Belgium, and some 20.9% in Austria[20]. Consequently, the figures from the ING survey on cryptocurrency ownership corroborate online surveys conducted by YouGov in the UK[21] and USA, and by Dalia Research in the US, UK, and

[20] The *Appendix Figures A1 and A2* present the demographic composition of my attitudes to cryptocurrencies. Each bar of the Appendix Figure A1 presents a decomposition of all four attitudinal variables by gender, overall and, then, for each of the 15 countries in my sample. Evidently, males are more likely to own cryptocurrencies and less likely not to have heard about them. This pattern exists in all countries in my sample. Lower participation rates by females have also been seen in equity investment (e.g. van Rooij at al., 2011) and other risky-asset investments (Almberg and Dreber, 2015). In the *Appendix Figure A2*, it is shown that the young are more likely to own cryptocurrencies and to intend to own in the future. The old are more likely not to intend to own in the future. Higher participation rates among the younger investors were also seen during the dot.com stock investing boom in the late 1990s (Greenwood and Nagel, 2008). The highly educated are more likely to own cryptocurrencies and less likely not to have heard about them. The self-employed and the employed are more likely to own cryptocurrencies. The inactive and the unemployed are the groups more likely not to have heard about them. Respondents in higher income groups are more likely to own cryptocurrencies, and they are less likely not to have heard about them. However, they are also the groups that are more likely not to intend to own cryptocurrencies in the future.

[21] It is worth noting that the Financial Conduct Authority (2019) reports a lower figure for ownership of some 3% in the UK and a higher figure of 70% for unawareness of cryptocurrencies, based on a face-to-face survey conducted in mid-December 2018.

Germany (Yougov, 2018a; b; 2019; Rauchs, et al., 2018; Jakubauskas, 2018). The latter also report figures for Brazil, Japan, South Korea, China and India.

3.3.3 Empirical strategy

Starting with the notable variation in the descriptive statistics on attitudes to cryptocurrencies across countries, I then examine the relationship between financial literacy and attitudes to cryptocurrencies using regression analysis. Then, I also examine the specifics of this relationship, in terms of the moderating factors. The ING 2018 International Survey on Mobile Banking did not include specific questions regarding financial knowledge. Hence, I generate an external proxy for financial literacy for the individuals in my sample, based on their individual demographic and country profile[22]. I merge the observations on individuals in my sample with disaggregated financial literacy figures from the Standard & Poor's Ratings Services Global Financial Literacy Survey[23]. The merging is conducted at the individual level based on the score by gender, age group (15-34, 35-54, ≥55), and income group (top 60%/bottom 40%) for each country[24].

The survey included five financial literacy questions covering the four fundamental financial concepts, i.e. interest (numeracy), interest compounding, inflation (money illusion), and the understanding of financial risk (Klapper et al., 2015). The disaggregated financial literacy figures I utilise approximate the probability of an individual in a given country of a specific gender, age and income group knowing at least 3 out of 4 concepts,

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22 The advantage of using an external financial literacy proxy is that the variable is an exogenous approximation of financial knowledge. The obvious limitation is that it is an approximation of individual-level financial literacy.

23 The Standard & Poor's Ratings Services Global Financial Literacy Survey conducted the world's largest and most comprehensive global measurement of financial literacy. It probed knowledge of four basic financial concepts: numeracy, interest compounding, inflation, and risk diversification. The survey is based on interviews with more than 150,000 adults in over 140 countries. The survey was implemented in 2014, as a collaboration between McGraw Hill Financial, Gallup, Inc., the World Bank Development Research Group, and the Global Financial Literacy Excellence Centre at the George Washington University.

24 The disaggregated statistics for each of the 4 constituent concepts of financial literacy by gender, age and income group for of the 15 countries in my sample are shown in the *Appendix 1 Table A3*. Data for all countries in the S&P Global Financial Literacy Survey are publicly available at:

https://www.cssf.lu/fileadmin/files/Protection_consommateurs/Education_financiere/SP_Ratings_Global_FinLit-Summary_Statistics_as_of_12152015.xls by answering correctly to the related questions[25]. my primary financial literacy proxy is the average score by gender, age, and income in each country. I get 180 distinctive financial-literacy profiles, i.e. 15*2*3*2, for the individuals in the ING 2018 International Survey.

Figure 3.5 presents scatterplots for the four response categories in the attitudes to cryptocurrencies, with financial literacy at the country level on the horizontal axis. The four scatterplots indicate a modest negative relationship between financial literacy and ownership of cryptocurrencies, and a stronger negative relationship between financial literacy and the intention to own cryptocurrencies in the future. On the bottom two scatterplots there is a stronger positive association between financial literacy and the negative inclination towards ownership of cryptocurrencies in the future. There is also a positive association between financial literacy country scores and the likelihood of not having heard of cryptocurrencies. On the left-hand side of all four scatterplots are Romania and Turkey, with low financial literacy country scores and higher rates for cryptocurrency ownership and the inclination to own. At the very right of all scatterplots are Australia, Germany, the United Kingdom, and the Netherlands, with high financial literacy country scores and low ownership and inclination-to-own rates.

[25] The exact wording of the questions was: (1) Risk diversification: "*Suppose you have some money. Is it safer to put your money into one business or investment, or to put your money into multiple businesses or investments?*". The response categories were: (i) *one business or investment*; (ii) *multiple businesses or investments*; (iii) *I don't know*; (iv) *refused to answer*. (2) Inflation: "*Suppose over the next 10 years the prices of the things you buy double. If your income also doubles, will you be able to buy less than you can buy today, the same as you can buy today, or more than you can buy today*"? The response categories were: (i) *less*; (ii) *the same*; (iii) *more*; (iv) *I don't know*; (v) *refused to answer*. (3) Numeracy (interest): "*Suppose you need to borrow 100 US dollars. Which is the lower amount to pay back 105 US dollars or 100 US dollars plus three percent*"? The response categories were: (i) *105 US dollars*; (ii) *100 US dollars plus three percent*; (iii) *I don't know*; (iv) *refused to answer*. (4a) Compound interest I: "*Suppose you put money in the bank for two years and the bank agrees to add 15 percent per year to your account. Will the bank add more money to your account the second year than it did the first year, or will it add the same amount of money both years*"? The response categories were: (i) *more*; (ii) *the same*; (iii) *I don't know*; (iv) *refused to answer*. (4b) Compound interest II: "*Suppose you had 100 US dollars in a savings account and the bank adds 10 percent per year to the account. How much money would you have in the account after five years if you did not remove any money from the account*"? The response categories were: (i) *more than 150 dollars*; (ii) *exactly 150 dollars*; (iii) *less than 150 dollars*; (iv) *I don't know*; (v) *refused to answer*.

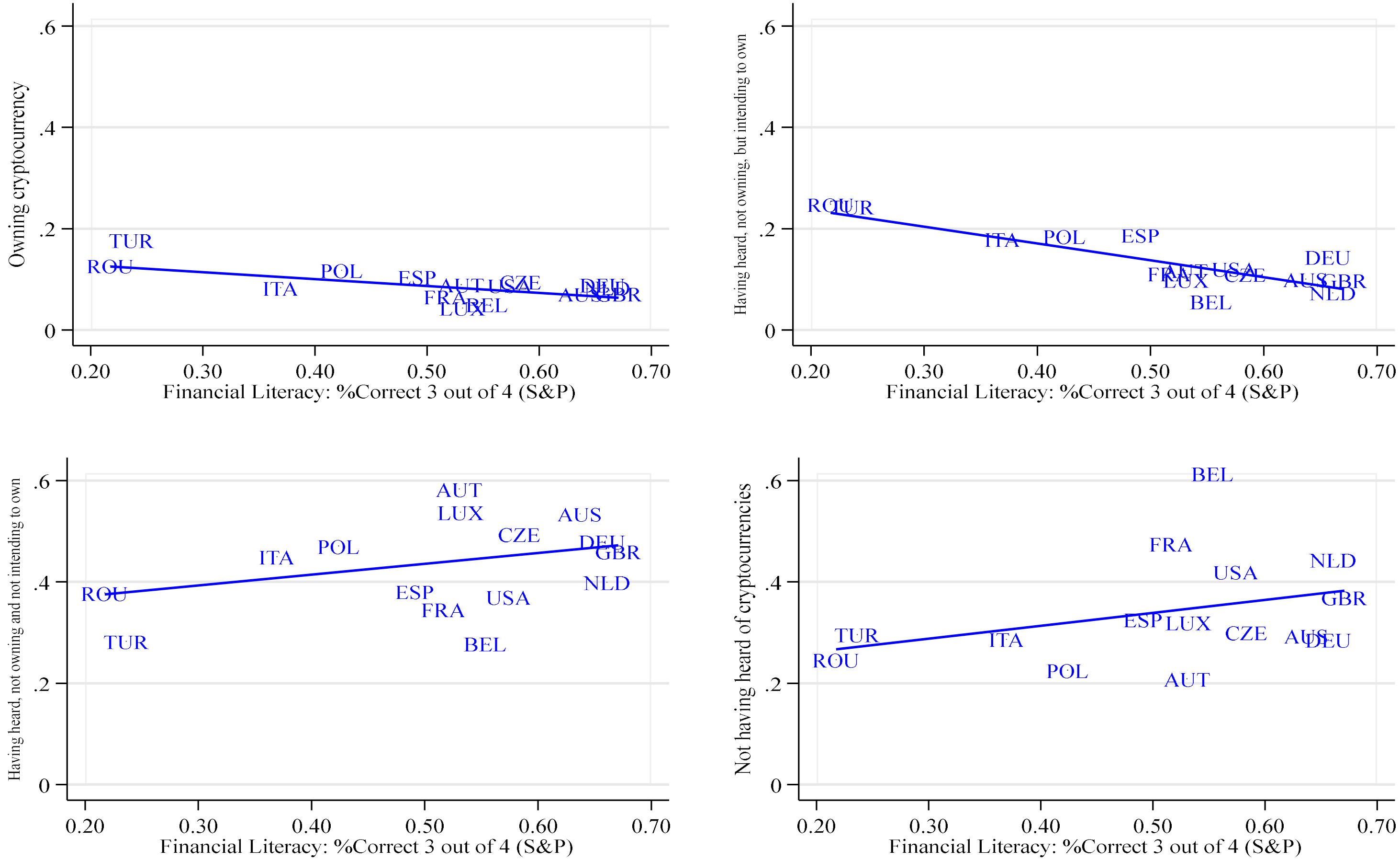

Figure 3.5

Attitudes to cryptocurrencies and financial literacy at the country level

This figure presents two-way scatterplots between the four response categories in the question regarding attitudes to cryptocurrencies, and financial literacy scores at the country level. Figures are weighted by GDP per capita (PPP current international dollar) from the World Bank's World Development Indicators. Financial literacy figures are from the S&P 2014 Global Financial Literacy Survey, and represent the percentage of individuals who responded correctly to at least 3 out of 4 concepts in each of the 15 countries in my sample.

Following the indicative figures based on country-level scores of financial literacy, I then examine the relationship between financial literacy and attitudes to cryptocurrencies at the individual level. I estimate weighted multinomial probit regressions (McFadden, 1989) for attitudes to cryptocurrencies, using a proxy for financial literacy at the individual level as my main explanatory variable. I also utilise a rich set of control variables for individual characteristics in my specifications. I estimate specifications of the following form for attitudes to cryptocurrencies:

$$AC_i = \beta_1 (FL_i) + \beta_2 X_i + \vartheta_r + \varepsilon_i, \tag{1}$$

where: AC_i is a 4-category variable capturing attitudes to cryptocurrencies for individual i, FL_i is a variable capturing financial literacy, X_i is a vector of individual characteristics, θ_r is a fixed effect for country of residence and ε_i is the usual error term.

The list of control variables in the vector X_j includes demographic characteristics, namely gender, a 3rd order polynomial in PPP-divided household income per capita, 6 age-group dummy variables, 4 dummy variables for marital status, a household size variable, 5 dummy variables for the level of education, and 7 dummy variables for occupational status. These variables are described in detail in *Table 3.1*. In addition, I generate three additional variables capturing digital literacy, preference for cash, and the inflectional FTR of the respondent's language. A strong inflectional FTR indicates an inclination for present-biased beliefs. Moreover, I generate variables for the sources of financial advice on cryptocurrencies, and the perceptions of the reward and risk involved in cryptocurrencies. These variables, which entail proxies for the factors that could moderate the effect of financial literacy on attitudes to cryptocurrencies, are described in detail in the following sub-section.

In additional specifications, I examine the explanatory power of specific moderating factors, M_i, which are likely to moderate the impact of financial literacy on attitudes to cryptocurrencies, i.e.:

$$AC_i = \beta_1(FL_i) + \beta_2 M_i + \beta_3(FL_i)M_i + \beta_4 X_i + \theta_r + \varepsilon_i, \tag{2}$$

I are interested in whether the effect of FL_i retains significance and magnitude after the inclusion of the interaction term with the moderating variable or not. These moderating variables are discussed in detail in sub-section 3.6.

3.3.4 Main control variables and related summary statistics

Table 3.1 presents my primary list of explanatory variables from the ING Mobile Banking Survey and their weighted summary statistics. The figures are presented overall (Column 1), for individuals who own cryptocurrencies (Column 2), for individuals who do not own cryptocurrencies but intend to in the future (Column 3), for respondents who do not intend to own cryptocurrencies in the future (Column 4), and for individuals who have never heard of cryptocurrencies (Column 5). Column 6 presents the difference in the figures between individuals who own or intend to own cryptocurrencies and those who do not intend to own or have never heard of cryptocurrencies, along with a weighted t-test for differences in averages[26]. The table shows that my financial-literacy proxy, which captures the probability of knowing at least 3 out of 4 financial literacy concepts, entails lower figures along individuals owning and intending to own cryptocurrencies, compared to individuals who do not intend to own or have never heard of cryptocurrencies. The mean difference between the two groups is negative and statistically significant at the 1% level. This observation matches well with the scatterplots for attitudes and financial literacy scores at the country level shown in Figure 3.5.

[26] The weighted t-test is computed via the parmby and metaparm commands in Stata (Newson, 2008).

Table 3.1

Weighted summary statistics

This table reports weighted averages for all individuals in the ING 2018 International Survey on Mobile Banking (Column 1). It reports weighted averages for individuals owning cryptocurrency (Column 2), for individuals intending to own cryptocurrency in the future (Column 3), for those not intending to own (Column 4), and for individuals who have not heard of cryptocurrencies before (Column 5). Column 6 reports mean differences and asterisks for the levels of significance from weighted t-tests between individuals currently owning or expecting to own cryptocurrencies in the future and those not intending to own or who have not heard of cryptocurrencies before. Weighted t-tests and levels of significance are computed using the parmby and metaparm commands in Stata. The asterisks denote the following levels of significance: *** p<0.01, ** p<0.05, * p<0.1. The financial literacy variable is calculated as a individual average of the country financial literacy scores by gender, age group (15-34, 35-54, >55) and income (top 60%, bottom 40%) from the S&P 2014Global Financial Literacy Survey.

	(1) All	(2) Owning	(3) Intend to own	(4) Not intend to own	(5) Not having heard of	(6) Difference: 1/2 – 3/4	
	[100.0%]	*[9.22%]*	*[13.96%]*	*[42.65%]*	*[34.17%]*		
Panel A: Full sample							
Number of observations	*13,267*	*1,223*	*1,852*	*5,659*	*4,533*		
Financial literacy	0.514	0.486	0.469	0.529	0.521	-0.050	***
Digital literacy	0.478	0.578	0.543	0.469	0.436	0.103	***
Preference for cash	0.835	0.897	0.905	0.818	0.811	0.087	***
Inflectional FTR	0.334	0.362	0.409	0.287	0.353	0.074	***
Household income per capita	1,078.3	1,047.8	970.9	1,171.7	1,015.2	-84.1	***
Missing income	10.6%	4.5%	6.5%	10.7%	13.8%	-0.064	***
Male	48.6%	68.1%	60.5%	54.3%	31.1%	0.195	***
Age	42.05	37.53	38.08	43.86	42.67	-5.467	***
Young (<45)	54.5%	70.6%	66.7%	48.8%	52.3%	0.179	***
Married	49.7%	52.4%	48.7%	49.8%	49.2%	0.007	
Single	22.9%	21.5%	26.1%	23.2%	21.6%	0.018	**
In a relationship	17.5%	19.3%	17.9%	16.9%	17.6%	0.012	
Widowed/Divorced/Separated	9.9%	6.8%	7.4%	10.1%	11.6%	-0.036	***
Household size	2.70	2.89	2.88	2.59	2.70	0.242	***
Panel B: Sub-sample of individuals who have heard of cryptocurrencies before							
Number of observations	*8,734*	*1,223*	*1,852*	*5,659*	–		
Fin. advice: An independent financial advisor	19.8%	18.3%	28.6%	17.2%	17.2%	0.073	***
–”– My friends/family	8.1%	12.4%	11.5%	6.1%	6.1%	0.058	***
–”– The internet and specialist websites	27.8%	45.1%	39.5%	20.1%	20.1%	0.216	***
–”– An online computer program or algorithm for tailored advice	6.7%	15.4%	10.6%	3.6%	3.6%	0.090	***
–”– No financial advice	37.6%	8.9%	9.8%	53.1%	53.1%	-0.437	***
Reward perception	0.602	0.784	0.744	0.515	0.515	0.245	***
Risk perception	0.732	0.659	0.686	0.764	0.764	-0.089	***
Digital currencies – e.g. bitcoin – are the future of spending online	3.003	3.939	3.757	2.547	2.547	1.282	***
–”– of investment as storage of value	2.953	3.876	3.710	2.498	2.498	1.278	***
I think the value of digital currencies – e.g. bitcoin – will increase in the next 12 months	3.072	3.939	3.687	2.677	2.677	1.110	***
Cryptocurrency riskier than cash	3.870	3.496	3.642	4.027	4.027	-0.443	***
- ” - bonds	3.682	3.287	3.462	3.842	3.842	-0.449	***
- ” - stocks	3.259	2.905	2.937	3.444	3.444	-0.519	***
- ” - real estate/funds	3.747	3.390	3.527	3.898	3.898	-0.425	***
- ” - gold	3.907	3.537	3.749	4.041	4.041	-0.376	***
- ” - investing in own business	3.509	3.159	3.261	3.668	3.668	-0.448	***

In terms of demographic characteristics, the average PPP-divided monthly household income per capita in the sample is €1,078.3, with owners and prospective owners of cryptocurrencies being poorer by some €84 per month on average. Individuals intending to own cryptocurrencies in the future have approximately €200 per month less income than individuals who have heard of cryptocurrencies but do not intend to own them. 48.6% of the sample are males, with 68.1% of owners and 60.5% of prospective owners being males. 31.1% of those who have never heard of cryptocurrencies are males. The average age in the sample is 42 years, with the sample of owners and prospective owners being significantly younger. The average age among owners is 37.5 years, and the figure for prospective owners is 38.1 years. The average age for those not intending to own is 43.9 years, and it is 42.7 years for those who have never heard of cryptocurrencies. 49.7% of the sample are married, 22.9% are single, 17.5% are in a relationship, and 9.9% are widowed or divorced/separated.

3.5 *Proxies for moderating factors and related summary statistics*

First, I compute a variable capturing digital literacy, as the number of items owned among the following: (1) Smartphone; (2) Tablet; (3) Smart TV; (4) Mobile phone (but not a smartphone); (5) Wearable device (such as an Apple Watch). This is converted into an index via dividing by 5. The figures in Table 1 indicate that individuals owning and intending to own score higher in terms of digital literacy, compared to individuals who do not intend to own or have never heard of cryptocurrencies before. Individuals who are more familiar with technology can be thought of as more likely to be aware of cryptocurrencies and the underlying technology that supports them. For instance, Giudici, *et al.* (2018) study the success rates of Initial Coin Offerings (ICOs) and find that the availability of their source code is positively and significantly associated with reports of successful asset raising.

Second, I also generate a variable capturing preference for cash by counting the number of different types of payment usually made in cash, among the following: (1) Rent/mortgage; (2) Utilities (e.g. electricity, gas); (3) Lunch/coffee/snack; (4) Regular (weekly) grocery/food shopping; (5) Restaurant; (6) Public transport (subway, bus); (7) Taxis; (8) Gifts; (9) Pocket money; (10) Lending money to a friend or family member. The count is converted into an index by dividing by 10. I consider the preference for cash as indicative of a certain tendency towards informal practices and payments in countries with well-developed financial markets and relatively high levels of financial inclusion. Rogoff (2016) points out that cash is also largely anonymous, i.e. it can only be traced through large serial numbers, and it has traditionally played an important role in facilitating crime and illegal trade. Hence, a higher preference for cash might be thought of as a proxy for inclination to informal practices and payments. In Table 3.1, owners and prospective owners of cryptocurrencies score higher in the preference for cash, compared to those who are negatively inclined or have not heard of cryptocurrencies. While this significant mean difference could be driven by the younger or the more digitally literate, the lower figure for preference for cash among those who have heard but do not intend to own cryptocurrencies could be indicating a positive correlation between cryptocurrency and inclination to informality.

Third, I generate a variable for intertemporal preferences or present-biased beliefs, captured via the future time-reference of the respondent's language or *inflectional FTR*. The inflectional FTR data for the languages in my sample is provided in Chen (2013)[27]. He finds that the languages that grammatically associate the future and the present foster future-oriented behavior and shows that speakers of such languages exhibit less risky behavior, i.e. save more, retire with more wealth, smoke less, practice safer sex, and are less obese. The inflectional FTR is a dummy variable taking the value 1 for 4 out of 11 languages in the ING 2018 International Survey, namely French, Italian, Spanish, and Turkish. The remaining 7 languages, namely German, English, Luxembourgish, Dutch, Polish, Romanian, and Czech, take the value 0. The figures in Table 3.1 indicate a significantly higher inflectional FTR among owners and prospective owners of cryptocurrencies, compared to the remaining sample, i.e. the future time-reference of respondents' language is higher among those owning and intending to own cryptocurrencies.

Fourth, I generate a set of proxies for the sources of financial advice on investment and cryptocurrencies. These questions were asked to the sub-sample of the 8,734 individuals who had heard of cryptocurrencies before. Individuals who had heard of cryptocurrencies before were presented with the following question: '*If you had money available (about 1 month's take-home/net pay) and you wanted some more information on cryptocurrency as a possible investment, where would you most likely get advice*'*?* The response options involved the following categories: (1) An independent financial advisor or bank advisor; (2) My friends/My family; (3) The internet and specialist websites; (4) An online computer program or algorithm that provides tailored advice; (5) I (would) never invest money in cryptocurrency; (6) I don't know. Intuitively, individuals with

[27] Languages where verbs have distinct future forms are said to have an "inflectional" future. The original source data on inflectional futures is from Dahl (1985) and Dahl and Velupillai (2011).

higher financial literacy are more capable to assess the quality of financial advice. Hence, it could be the case that financial advice on cryptocurrencies could be moderating any effect of financial literacy on the demand for cryptocurrencies.

Advice from friends and family has been described as an informal source of investment information (Stolper and Walter, 2017). Evidence suggests that individuals are more likely to initiate stock market investment if their neighbors have recently experienced good returns[28]. On the other hand, Haliassos, et al. (2020) find that exogenous exposure to more financially literate neighbors promotes saving in private retirement accounts and stockholding, primarily for educated households and via substantial interaction and knowledge transfer possibilities. Previous literature has shown that the more financially literate are better able to seek for appropriate financial advice on financial matters (e.g. Calcagno and Monticone, 2015; Stolper, 2018). Hilgert, et al. (2003) find that households with higher financial practice index scores hold a preference on sourcing information on financial service over the internet than other media outlets.

In terms of access to financial advice, 19.8% of the sample would receive financial advice for investment in cryptocurrencies from an independent financial advisor or bank advisor, 8.1% would seek such advice from friends and family, 27.8% would look for advice on cryptocurrencies from the internet and specialist websites, and 6.7% would utilise an online computer program or algorithm for tailored advice on investment in cryptocurrencies. A remaining 37.6% of the sample would not look for financial advice or would not know where to look for financial advice on cryptocurrencies. There are notable differences between owners/prospective owners of cryptocurrencies and the rest, in terms of the likelihood of using the internet and specialist websites for financial advice. Moreover, owners and prospective owners are significantly less likely than non-owners and those who have never heard of cryptocurrencies to report that they have not used any financial advice and that they do not know where to seek for financial advice.

Fifth, I generate proxies for the perceptions of reward and risk of investment in cryptocurrencies. There were two specific questions in the 2018 ING Mobile Banking survey that enable the examination of these moderators. These questions were asked to the sub-sample of the 8,734 individuals who had heard of cryptocurrencies before. my reward proxy originates in the

[28] In a field experiment, Bursztyn, et al. (2014) show that apart from the learning effect, such peer effects can arise because one's utility of owning an asset is directly affected by whether a peer owns the asset, due to relative wealth considerations or the pleasure of being able to talk about a commonly held investment.

following question: "*Crypto-money or cryptocurrency is a kind of digital currency. This currency is not created nor secured by the government, but by a network of individuals. Bitcoin is the best-known example. Please indicate how much you agree or disagree with the following statements*":

- "Digital currencies – such as bitcoins – are the future of spending online".
- "Digital currencies – such as bitcoins – are the future of investment as storage of value".
- "I think the value of digital currencies – such as bitcoins – will increase in the next 12 months".

I reverse the order of the six grid options offered for each item in the original survey, so that responses signify: (1) Strongly disagree; (2) Disagree; (3) Neither agree or disagree/I don't have an opinion; (4) Agree; (5) Strongly agree[29]. In Table 3.1, the perceptions of reward are notably higher among owners and prospective owners of cryptocurrencies, compared to the rest. Owners and prospective owners of cryptocurrencies are significantly more likely to believe that digital currencies, such as bitcoin, are the future of spending online, the future of investment as storage of value. Moreover, noting that the survey took place in mid-2018, the former are more likely to believe that the value of digital currencies, such as bitcoin, will increase in the next 12 months, compared to individuals who do not intend to own or have never heard of cryptocurrencies[30].

Finally, my proxy for the perception of the risk of cryptocurrencies stems from the following question: "*Cryptocurrencies are a type of asset. How would you compare the risk of owning cryptocurrency compared to the following alternative assets*"?

- Cash
- Government bonds

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[29] The *Appendix Figure A3* presents in bars the frequencies of responses for each of the three statements. Panel A presents the frequencies of each of the five categories. Panel B presents the percentage of individuals who strongly agree or agree with each of the three statements. Weighted frequencies are presented overall and by country. Overall, less than a third of the sample agree or strongly agree with the view that digital currencies are the future of spending, the future of investment as storage of value, and with the view that their value will increase in the next 12 months. It is also the case that about one third of the overall sample strongly disagrees or disagrees with each of the statements. About 40% of the sample neither agrees or disagrees or has no view on the prospects of cryptocurrencies. In Panel B, it is worth noting that individuals in Australia, the Netherlands, Luxembourg, Austria and Belgium appear more skeptical regarding the prospects of cryptocurrencies in all three aspects. The figures on reward prospects in the 3 aspects are relatively low in Turkey too, despite the high rates of ownership of cryptocurrency in the country. This might indicate that the respondents in Turkey value highly other attributes in cryptocurrency usage, e.g. they might see it as a hedging instrument in view of the large devaluations of the Turkish Lira.

[30] In the *Appendix 1 Table A4*, I present the average of the key variables from the ING sample, distinguishing between individuals of high and low financial literacy within each country, i.e. those for which the percentile of the financial literacy score is greater than the 50^{th} percentile within each country or lower/equal to the 50^{th} percentile in that country. It is shown that the highly literate group within each country has lower scores on all 3 reward perceptions of cryptocurrencies. These associations are also confirmed in the weighted pairwise correlation matrix in the *Appendix 1 Table A5*.

- Stock market investment
- Real estate / property funds
- Gold
- Investing in your own business

I reverse the order of the five grid options offered for each item, so that responses signify the following: (1) Holding cryptocurrency entails much lower risk compared to holding … [the alternative asset]; (2) Holding cryptocurrency entails lower risk compared to holding …; (3) Holding cryptocurrency entails about the same risk as holding …; (4) Holding cryptocurrency entails higher risk compared to holding …; (5) Holding cryptocurrency entails much higher risk compared to holding … [the alternative asset].[31] In Table 3.1, it is shown that, compared to the rest of respondents, owners and prospective owners of cryptocurrency are significantly less likely to believe that cryptocurrencies, such as bitcoin are riskier than cash, bonds, stocks, real estate/funds, gold, and investment in one's own business[32].

3.3.6 The OECD 2019 Consumer Insights Survey on Cryptoassets

I utilise a second novel survey, in order to establish the external validity of my results, particularly with respect to the financial literacy proxy used in my analysis. I use microdata from 3 countries from the OECD 2019 Consumer Insights Survey on Cryptoassets (OECD, 2019). The survey is based on a custom-built questionnaire, which was designed to survey retail investors/consumers, in order to collect data on their attitudes, behaviors and experiences towards digital financial assets, specifically digital (or crypto) currencies and initial coin offerings. In 2019, the survey was conducted in three Asia-Pacific jurisdictions with funding support from the Japanese Government. A research analytics provider was commissioned to translate the questionnaire into local languages and administer it via online channels among retail investors across Malaysia, the Philippines and Vietnam. This survey, which was conducted in February and March 2019, lasted between 15 and 20 minutes per respondent. It was self-administered.

[31] The *Appendix Figure A4* presents the weighted frequencies of responses for my risk proxy question. Panel A presents the response figures in each of the five categories for the risk comparison with each of the six alternative assets. Panel B presents the percentage of individuals who find that cryptocurrency is much riskier or riskier than each of the alternative assets. Overall, 71% find that cryptocurrency is much riskier or riskier than cash, 64.1% find it is much riskier or riskier than bonds, 47.3% find it is much riskier or riskier than stocks, 66.5% find it is much riskier or riskier than real estate, 71.8% find it is much riskier or riskier than gold, and 59.3% find it is much riskier or riskier than investing in one's own business.

[32] In the *Appendix Table A4*, it is also shown that the individuals in the high literacy group within each country give higher scores on all six risk perceptions of cryptocurrencies. These associations are also confirmed in the weighted pairwise correlation matrix in the *Appendix Table A5*.

A two-stage sampling approach was used in the research design. The core survey was based on an online sample of 3,006 respondents aged 18 and over, living in Malaysia, the Philippines and Vietnam (over 1,000 per country). Hard quotas were set on age and gender, and soft quotas on income, to ensure that the sample was representative of the online adult population in each country. This was supplemented by a booster sample of individuals who had ever invested in cryptoassets. The booster sample was used to increase the robustness of the sample for analysis and provide valuable information on the purchase process and behaviour concerning cryptoassets. The respondents included a diversified range of consumers across age, gender, income and education. The final sample comprises of 3,428 individuals, 2,979 of which are from the main sample and 449 from the booster sample. 1,138 of the respondents are from Malaysia, 1,144 are from the Philippines, and 1,146 are from Vietnam. 49.8% of the pooled sample are male and the average age is 36.1 years. 58.2% are homeowners, 63.9% are employed full-time, 5.5% are employed part-time, and 12.4% are self-employed. 57.9% have a University degree, and another 11.7% have a postgraduate qualification. The average monthly household income is 4,318 international dollars or 1,510 US dollars[33].

As the OECD 2019 Consumer Insights Survey on Cryptoassets comprises retail investors who are more likely to engage with cryptoassets, there I have 36.8% of investors currently owning cryptocurrencies, with the figures being 27.2% in Malaysia, 35.5% in the Philippines, and 37.3% in Vietnam (shown in the *Appendix 1 Table A2*). 14.6% of the sample previously held cryptocurrencies but do not hold them anymore. The figures for previous owners are 13.9% in Malaysia, 12.8% in the Philippines, and 17.1% in Vietnam. 31.1% of the OECD sample have never held cryptocurrencies, with the figures being 41.9% in Malaysia, 25.4% in the Philippines, and 26% in Vietnam. Finally, 17.5% of the retail investor sample have never heard of cryptocurrencies, with the figures being 14.1% in Malaysia, 22.6% in the Philippines, and 15.9% in Vietnam.

I can corroborate the OECD sample from Chen et al. (2021) study on "Gender Gap in Fintech" with postulating the higher female participation into cryptocurrency ownership in the Philippines, Malaysia and Vietnam. The study also shows higher participation into fintech in general in countries such as India and China that have large younger populations and more recently

[33] The Appendix 1 Table A2 presents the respective summary statistics for variables used in the analysis of the OECD 2019 Consumer Insights Survey on Cryptoassets. There, the summary statistics are presented for the pooled sample of 3 countries, and for each of the different 4 categories of the dependent variable for attitudes to cryptocurrencies, for instance, for current owners, previous owners, those who never held, and those whose who never heard of cryptocurrencies.

establishing financial services with less technological path dependency that may aid in adaptation digitalised financial services.

3.4. Financial literacy and attitudes to cryptocurrencies

3.4.1 Does financial literacy affect the demand for cryptocurrencies?

Table 3.2 presents my baseline estimates of the relationship between financial literacy and attitudes to cryptocurrencies. Marginal effects and robust standard errors are shown in brackets for the four response categories of my dependent variable, namely owning cryptocurrencies (Column 1), not owning but intending to own in the future (Column 2), not owning and not intending to own in the future (Column 3), and not having heard of cryptocurrencies before (4). The estimation method is a weighted multinomial probit regression. The error terms are assumed to be independent, standard normal, random variables. The multinomial probit model is the most suitable model to estimate attitudes to cryptocurrencies, as, unlike the multinomial logit, it does not suffer from the Independence of Irrelevant Alternatives (IIA) assumption. For financial choice models, omitting that assumption is of realistic benefit[34]. A further advantage of using the multinomial probit model to study the relationship between financial literacy and attitudes to cryptocurrencies lies with the ability to use all the information available, including answers from those respondents who do not identify with cryptocurrencies, because they have not heard of them before.

[34] For instance, the assumption would signify that omitting the category for those who have not heard of cryptocurrencies before would induce the proportionate allocation of responses from the omitted category to the remaining categories, based on their observed frequencies.

Table 3.2

Attitudes to cryptocurrencies and financial literacy

This table reports estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies and robust standard errors are presented in brackets. The specification also includes a constant term. The % Fin. Literacy effect is calculated as the change in the predicted probability by an increase in the financial literacy score from 0.5177 to 0.61.77. The %Interquartile-change effect is calculated as the change in the predicted probability by an increase in financial literacy from 0.442 to 0.6233. The asterisks denote the following levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***
	(1)	(2)	(3)	(4)
Financial literacy	-0.300***	0.084	0.668***	-0.452***
	[0.116]	[0.135]	[0.190]	[0.175]
Digital literacy	0.120***	0.133***	-0.078***	-0.175***
	[0.012]	[0.014]	[0.021]	[0.019]
Inflectional FTR	-0.008	0.130***	-0.042	-0.080***
	[0.019]	[0.025]	[0.028]	[0.024]
Preference for cash	0.012**	0.002	-0.042***	0.029***
	[0.006]	[0.006]	[0.009]	[0.009]
Male	0.067***	0.049***	0.075***	-0.192***
	[0.006]	[0.007]	[0.010]	[0.009]
Log(Household income per capita)	-0.015	-0.010	-0.078***	0.102***
	[0.018]	[0.020]	[0.030]	[0.026]
Log(Household income per capita)^2	0.004	0.004	0.023***	-0.031***
	[0.005]	[0.006]	[0.008]	[0.007]
Log(Household income per capita)^3	-0.001	-0.001	-0.002***	0.002***
	[0.000]	[0.000]	[0.001]	[0.001]
Missing household income per capita	-0.039*	-0.02	0.033	0.026
	[0.021]	[0.023]	[0.032]	[0.027]
Age: 18-25	0.071***	0.073***	-0.160***	0.016
	[0.012]	[0.014]	[0.019]	[0.017]
–”– 26-35	0.073***	0.051***	-0.156***	0.032**
	[0.010]	[0.011]	[0.015]	[0.014]
–”– 36-45	0.041***	0.026**	-0.099***	0.032**
	[0.010]	[0.011]	[0.015]	[0.014]
–”– 46-55	0.027***	0.009	-0.056***	0.02
	[0.010]	[0.011]	[0.014]	[0.013]
–”– 56-65	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Married/Cohabiting/Civil partnership	0.005	-0.022**	-0.025*	0.041***
	[0.008]	[0.009]	[0.013]	[0.012]
In a relationship	0.008	-0.019**	-0.011	0.023*
	[0.008]	[0.009]	[0.014]	[0.013]
Widowed/Divorced/Separated	0.024**	0.004	-0.052***	0.024
	[0.012]	[0.013]	[0.017]	[0.016]
Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	0.006*	0.009***	-0.015***	-0.001
	[0.003]	[0.004]	[0.005]	[0.005]
Pre-sixteen education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
A-levels, GNVQ or college	0.021**	-0.008	0.055***	-0.068***
	[0.010]	[0.011]	[0.015]	[0.013]
Higher vocational education or HND	0.028**	0.011	0.066***	-0.104***
	[0.011]	[0.012]	[0.017]	[0.015]

Table 3.2 continued in next page

Table 3.2 continued from last page

	(1)	(2)	(3)	(4)
University (Bachelors)	0.032***	0.020*	0.120***	-0.172***
	[0.011]	[0.012]	[0.017]	[0.015]
Higher university degree	0.055***	0.016	0.141***	-0.212***
	[0.011]	[0.013]	[0.018]	[0.016]
Occupation: Self-Employed	0.051***	0.044**	-0.061**	-0.034
	[0.015]	[0.017]	[0.026]	[0.025]
–”– Full-time employee	0.024*	0.007	-0.073***	0.041**
	[0.012]	[0.014]	[0.021]	[0.019]
–”– Part-time employee	0.025*	0.006	-0.079***	0.047**
	[0.014]	[0.015]	[0.023]	[0.021]
–”– Student	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
–”– Unemployed	0.008	-0.007	-0.059**	0.058**
	[0.016]	[0.018]	[0.026]	[0.023]
–”– Inactive	0.009	-0.013	-0.055**	0.059***
	[0.015]	[0.017]	[0.024]	[0.022]
–”– Retired	0.022	-0.017	-0.068***	0.063***
	[0.017]	[0.019]	[0.026]	[0.024]
Country: Austria	0.006	0.145***	0.290***	-0.440***
	[0.017]	[0.026]	[0.028]	[0.024]
–”– Belgium	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
–”– France	-0.014	0.010	0.087***	-0.082***
	[0.020]	[0.022]	[0.030]	[0.025]
–”– Germany	0.041*	0.151***	0.094***	-0.286***
	[0.022]	[0.031]	[0.035]	[0.031]
–”– Italy	-0.042	0.067**	0.311***	-0.336***
	[0.028]	[0.031]	[0.044]	[0.040]
–”– Luxembourg	-0.054***	0.041	0.248***	-0.235***
	[0.021]	[0.025]	[0.030]	[0.027]
–”– Netherlands	0.053**	0.073**	0.026	-0.152***
	[0.022]	[0.031]	[0.035]	[0.030]
–”– Spain	-0.001	0.058***	0.160***	-0.217***
	[0.021]	[0.022]	[0.031]	[0.026]
–”– United Kingdom	0.015	0.092***	0.083**	-0.191***
	[0.021]	[0.031]	[0.035]	[0.031]
–”– Poland	0.001	0.206***	0.278***	-0.485***
	[0.021]	[0.030]	[0.036]	[0.032]
–”– Romania	-0.064	0.256***	0.334***	-0.525***
	[0.041]	[0.050]	[0.067]	[0.061]
–”– Czech Republic	0.049**	0.141***	0.263***	-0.454***
	[0.022]	[0.031]	[0.036]	[0.031]
–”– Turkey	-0.018	0.117**	0.276***	-0.374***
	[0.040]	[0.046]	[0.065]	[0.059]
–”– Australia	0.029	0.110***	0.160***	-0.299***
	[0.021]	[0.030]	[0.033]	[0.029]
–”– USA	0.014	0.129***	0.057**	-0.200***
	[0.017]	[0.026]	[0.028]	[0.023]
Predicted probability	*0.0931*	*0.1412*	*0.4247*	*0.3410*
%Fin. literacy effect	*-39.46%*	*4.76%*	*22.70%*	*-18.83%*
#Observations	13,267			
Log-likelihood	-14,574.9			
Wald χ^2	2,935.9***			

Our estimates confirm a negative relationship between financial literacy and ownership of cryptocurrencies. The relationship is economically and statistically significant at the 1% level. A one standard-deviation increase in the financial-literacy score of 0.1470 from the average of 0.5133 decreases the predicted probability of cryptocurrency ownership by 39.5%, i.e. by 3.71 percentage points − from 9.41% to 5.7%[35]. The more financially literate are more likely to have heard of cryptocurrencies, but do not intend to own them in the future. A one standard deviation increase in financial literacy increases the probability of having no intention of owning cryptocurrencies in the future by 22.7%. The more financially literate are less likely to report that they have not heard of cryptocurrencies before. A one standard deviation increase in financial literacy decreases the probability of not having heard of cryptocurrencies by 18.8% respectively.

The estimates of the remaining control variables show that digital literacy is positively and significantly associated with ownership and prospective ownership. It is negatively and significantly associated with negative inclination regarding future ownership and with ignorance regarding cryptocurrencies. A strong inflectional FTR is positively associated with the intention to own in the future and negatively associated with ignorance regarding cryptocurrencies. A higher preference for cash is positively associated with current ownership. It is negatively associated with negative inclination towards future ownership of cryptocurrencies. It is also positively associated with ignorance regarding cryptocurrencies. The first two patterns are likely to signify a positive association between informality and cryptocurrency ownership.

Males are less likely than females to report not having heard about cryptocurrencies, and they are both more likely to own and intend to own in the future, but they are also more likely than females to be negatively disposed towards them. The effects are of larger magnitudes for ownership and prospective future ownership. There is a negative non-linear (concave) relationship between income and negative inclination towards future cryptocurrency ownership. In contrast there is a positive convex relationship between income and ignorance about cryptocurrencies. In addition, younger groups are more likely to own and to intend to own cryptocurrencies, compared to their older counterparts.

[35] It is worth noting that the marginal effects of financial literacy reported in the tables implement a change by 1 unit, in a variable that ranges between 0.1833 and 0.7548. They are calculated over the entire distribution, not at the mean of other independent variables. Alternatively, one could multiply the financial-literacy variable by 10 and that would render the marginal effects of financial literacy closer to the calculated magnitudes.

The more highly educated are less likely to report not having heard about cryptocurrencies. They are more likely to own cryptocurrency at present. However, they are also more likely to have no intention to own in the future. The self-employed are much more likely to own and intend to own cryptocurrencies compared to students and all remaining labor market groups. Employed individuals are more likely to own and less likely not to intend to own cryptocurrencies, compared to students. They are also more likely to have heard about them. The unemployed, the inactive, and retirees are less likely not to intend to own cryptocurrencies in the future. They are also more likely to not have heard about them, compared to students.

Table 3.2 shows that more financially literate individuals are significantly less likely to own and more likely to have no intention of owning cryptocurrencies, despite the fact that they are more likely to be aware of them. This confirms the pattern observed in Figure 3.5, which illustrates that countries with lower financial literacy scores exhibit lower rates of ownership and prospective ownership of cryptocurrencies. In *Table 3.3*, I examine country variations in the relationship between financial literacy and my four response categories for attitudes to cryptocurrencies. I introduce a set of 15 interaction terms between countries and financial literacy.

Table 3.3

The interaction between financial-literacy and countries

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies and robust standard errors are presented in brackets. The remaining specification is identical to that of Table 3.2, and it also incorporates 15 interaction terms between financial literacy and country.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***
	(1)	(2)	(3)	(4)
Financial literacy	-1.264**	0.599	3.242***	-2.577***
	[0.607]	[0.855]	[0.952]	[0.782]
Austria	-1.160***	0.273	1.871***	-0.983*
	[0.393]	[0.548]	[0.633]	[0.552]
Belgium	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
France	-0.541	0.432	1.697***	-1.588***
	[0.392]	[0.532]	[0.619]	[0.506]
Germany	-0.599	0.458	1.677***	-1.536***
	[0.371]	[0.512]	[0.582]	[0.489]
Italy	-0.470	0.312	1.858***	-1.700***
	[0.352]	[0.494]	[0.551]	[0.454]
Luxembourg	-1.002*	0.571	1.370**	-0.939
	[0.544]	[0.583]	[0.679]	[0.597]
The Netherlands	-0.734*	0.04	1.586**	-0.892*
	[0.404]	[0.566]	[0.619]	[0.512]
Spain	-0.469	0.151	1.159*	-0.841
	[0.390]	[0.530]	[0.633]	[0.533]
United Kingdom	-1.111	1.514*	0.259	-0.662
	[0.713]	[0.848]	[1.058]	[0.922]
Poland	-0.479	0.479	1.554***	-1.554***
	[0.366]	[0.509]	[0.577]	[0.489]
Romania	-0.438	0.778	1.635***	-1.975***
	[0.360]	[0.505]	[0.573]	[0.478]
Czech Republic	-0.741*	0.479	0.453	-0.191
	[0.418]	[0.572]	[0.668]	[0.578]
Turkey	-0.422	0.649	1.525***	-1.752***
	[0.352]	[0.500]	[0.568]	[0.469]
Australia	-0.573	0.372	1.901***	-1.701***
	[0.365]	[0.515]	[0.575]	[0.479]
USA	-0.49	0.256	2.050***	-1.816***
	[0.369]	[0.519]	[0.589]	[0.484]
Fin. literacy*Austria	2.106***	-0.204	-2.790**	0.888
	[0.700]	[0.969]	[1.133]	[0.998]
Fin. literacy*Belgium	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
Fin. literacy*France	0.916	-0.762	-2.870***	2.715***
	[0.702]	[0.946]	[1.113]	[0.914]
Fin. literacy*Germany	1.096*	-0.535	-2.753***	2.192***
	[0.637]	[0.880]	[0.999]	[0.837]
Fin. literacy*Italy	0.643	-0.392	-2.819***	2.568***
	[0.639]	[0.883]	[1.003]	[0.840]
Fin. literacy*Luxembourg	1.696*	-0.949	-1.939	1.192
	[0.975]	[1.041]	[1.219]	[1.086]
Fin. literacy*Netherlands	1.310*	-0.038	-2.711***	1.439*
	[0.675]	[0.946]	[1.043]	[0.863]
Fin. literacy*Spain	0.796	-0.108	-1.654	0.965
	[0.708]	[0.951]	[1.158]	[0.987]

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	(1)	(2)	(3)	(4)
Fin. literacy*United Kingdom	1.817*	-2.185	-0.675	1.044
	[1.101]	[1.332]	[1.643]	[1.425]
Fin. literacy*Poland	0.804	-0.465	-2.144**	1.806*
	[0.674]	[0.917]	[1.072]	[0.931]
Fin. literacy*Romania	0.191	-1.519	-1.882	3.210***
	[0.774]	[1.014]	[1.295]	[1.135]
Fin. literacy*Czech Republic	1.381*	-0.577	-0.406	-0.398
	[0.725]	[0.989]	[1.160]	[1.006]
Fin. literacy*Turkey	0.344	-1.515	-1.722	2.893***
	[0.699]	[0.987]	[1.239]	[1.062]
Fin. literacy*Australia	1.042*	-0.469	-3.006***	2.434***
	[0.632]	[0.887]	[0.994]	[0.828]
Fin. literacy*USA	0.885	-0.232	-3.487***	2.833***
	[0.646]	[0.902]	[1.030]	[0.849]
Predicted probability	*0.0931*	*0.1413*	*0.4247*	*0.3409*
%Fin. literacy effect	*-73.97%*	*12.88%*	*83.58%*	*-59.98%*
#Observations		13,267		
Log-likelihood		-14,531.1		
Wald χ^2		2,966.7***		

The estimates confirm the robustness of my findings in Table 3.2, as the effect of financial literacy on cryptocurrency ownership remains negative and statistically significant at the 5% level. Moreover, it remains positive and statistically significant at the 1% level, with respect to the negative inclination to own in the future. It also remains negative and statistically significant at the 1% level when it comes to the probability of having heard of cryptocurrencies before. However, the country interactions also indicate heterogeneity in the effect of financial literacy on cryptocurrency ownership by country. There are positive effects on ownership from the interaction terms between financial literacy and residents of Austria, Germany, Luxembourg, the Netherlands, the UK, the Czech Republic, and Australia. The reference category in this comparative assessment is the interaction term with Belgium, i.e. the country with the lowest ownership rates[36].

[36] For completeness, I also present an additional robustness checks for education and risk preferences. *Appendix 1 Table A6*. Using the multinomial probit specification of Table 3.2, I replace the 5 education categories with a continuous variable capturing years of education. The continuous years of education variable is computed as follows: Individuals with 'Pre-sixteen education' get assigned with 9 years of education. Individuals with 'A-levels, GNVQ or college' get assigned with 12 years of education. Respondents with 'Higher vocational education or HND' get assigned with 14 years. Then, respondents with 'University (Bachelor)' get assigned with 16 years, and individuals with 'Higher university degree'

3.4.2 Robustness exercises

In this sub-section, I conduct a number of robustness exercises to confirm the validity of my primary findings, i.e. the negative relationship between financial literacy and cryptocurrency ownership, the positive relationship between financial literacy and the intention not to own cryptocurrencies in the future, and the negative relationship with lack of awareness of cryptocurrencies.

Our first robustness exercise in *Panel A* of *Table 3.4* replicates my primary estimation of Table 3.2, removing the individual weights used to make the sample estimates representative at the country level. In the unweighted estimation, financial literacy decreases the probability of cryptocurrency ownership by 44.9% and the effect is significant at the 5% level. The magnitudes of the effects of financial literacy are very similar to those of Table 3.2. The financial literate are more likely to have no intention of owning cryptocurrency in the future and the magnitude of the effect is 25.4%. In *Panel B*, I present estimates from unweighted multinomial probit regressions with bootstrapped standard errors, based on 1,000 replications. The exercise stems from the consideration that my financial literacy proxy is derived from an external database, i.e. the S&P 2014 Global Financial Literacy Survey and is matched to the ING Mobile Banking Survey based

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get assigned with 19 years. Then, I estimate, including a triple interaction term between financial literacy, years of education, and the logarithm of monthly PPP-divided household income per capita. I omit the 3rd order polynomial in income in this specification. The estimates of the Appendix 1 Table A6 confirm the robustness of my findings. This is also the case in models with separate interaction terms between financial literacy and the years of education, and financial literacy and income. *Appendix 1 Table A7* Individual's attitudes to risk stems from individual's risk preference, awareness and perception (e.g., Georgantzis and Tisserand, 2019; Attanasi 2018; Eckel and Grossman, 2008; Gerardo and Georgantzis 2002; Kahneman and Tversky, 1979). Financial literacy education is intended to enhance the understanding and perception of financial risk. To control for generic risk aversion, I present the Appendix Table A7 in which I interact financial literacy with the proxy for generic risk preferences, which is available at the OECD data (please note that no such proxy exists in the ING data). The OECD survey formulates the question with the choice of answer options the following: "To what extent do the following statements describe you?": "I am prepared to risk some of my own money when saving or making an investment". With answer options of three: "Describes me very well", "Describes me somewhat" or "Does not describe very well". The interaction effect of the financial literacy and risk preferences does not show significant result to cryptocurrency ownership behaviour or has a control impact on financial literacy effect. Hence, after further controlling for the education, income or risk preference, the finding on financial literacy effect is robust.

on gender, age and income categories. Any resulting ‘match bias’ could affect the standard errors of the multinomial probit regressions. The estimates with bootstrapped standard errors confirm the robustness of my findings. There is a negative effect of financial literacy on cryptocurrency ownership, significant at the 5% level. There is a positive effect of financial literacy on the negative predisposition to own cryptocurrency in the future, significant at the 1% level. Moreover, financial literacy is positively related to awareness, there is a negative effect of financial literacy on not having heard about cryptocurrencies, significant at the 1% level.

Table 3.4

Robustness exercises

This table reports estimates of the effect of financial literacy on attitudes to cryptocurrencies from 9 distinctive weighted multinomial probit regressions. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies and robust standard errors are presented in brackets. The remaining specification of all models is identical to that of Table 3.2.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***
Panel A: Unweighted estimation	(A_1)	(A_2)	(A_3)	(A_4)
Financial literacy	-0.279**	0.084	0.643***	-0.448***
	[0.114]	[0.132]	[0.188]	[0.173]
%Fin. literacy effect	*-44.92%*	*4.96%*	*25.40%*	*-22.95%*
Panel B: Unweighted estimation–Bootstrapped S.E.	(B_1)	(B_2)	(B_3)	(B_4)
Financial literacy	-0.279**	0.084	0.643***	-0.448**
	[0.112]	[0.132]	[0.197]	[0.175]
%Fin. literacy effect	*-44.92%*	*4.96%*	*25.40%*	*-22.95%*
Panel C: Bootstrapped estimation	(C_1)	(C_2)	(C_3)	(C_4)
Financial literacy	-0.280**	0.084	0.643***	-0.447**
	[0.112]	[0.133]	[0.197]	[0.175]
%Fin. literacy effect	*-44.80%*	*5.01%*	*25.41%*	*-22.94%*
Panel D: High financial-literacy by country indicator	(D_1)	(D_2)	(D_3)	(D_4)
High financial literacy by country	-0.015**	0.001	0.042***	-0.029***
	[0.006]	[0.007]	[0.011]	[0.010]
%Fin. literacy effect	*-15.86%*	*1.03%*	*9.87%*	*-8.39%*
Panel E: Logarithmic financial literacy	(E_1)	(E_2)	(E_3)	(E_4)
Log(Financial literacy)	-0.183***	-0.034	0.321***	-0.104
	[0.053]	[0.062]	[0.089]	[0.082]
%Fin. literacy effect	*-40.67%*	*-9.20%*	*17.81%*	*-8.71%*
Panel F: Alternative financial-literacy measure I	(F_1)	(F_2)	(F_3)	(F_4)
$FL_i^1 = \prod \frac{FL_{gender} FL_{age} FL_{income}}{FL_{country}^2}$	-0.086**	0.021	0.220***	-0.155***
	[0.036]	[0.042]	[0.060]	[0.057]
%Fin. literacy effect	*-15.72%*	*2.17%*	*9.29%*	*-8.13%*
Panel G: Alternative financial-literacy measure II	(G_1)	(G_2)	(G_3)	(G_4)
$FL_i^2 = \prod \frac{FL_{gender} FL_{age} FL_{income}}{FL_{country}^3}$	-0.052***	-0.009	0.100***	-0.039
	[0.016]	[0.019]	[0.027]	[0.026]
%Fin. literacy effect	*-11.07%*	*-1.41%*	*4.98%*	*-2.51%*
Panel H: Male sub-sample	(H_1)	(H_2)	(H_3)	(H_4)
Financial literacy	-0.517**	-0.212	1.024***	-0.295
	[0.215]	[0.241]	[0.315]	[0.256]
%Fin. Literacy effect	*-46.86%*	*-21.28%*	*30.55%*	*-20.26%*
Panel I: Female sub-sample	(I_1)	(I_2)	(I_3)	(I_4)
Financial literacy	-0.208	0.123	0.606**	-0.521*
	[0.143]	[0.181]	[0.285]	[0.292]
%Fin. literacy effect	*-42.86%*	*11.68%*	*22.46%*	*-16.00%*
Panel J: Excluding Turkey and Romania	(J_1)	(J_2)	(J_3)	(J_4)
Financial literacy	-0.195*	0.108	0.689***	-0.601***
	[0.116]	[0.133]	[0.202]	[0.186]
%Fin. literacy effect	*-21.25%*	*7.25%*	*15.08%*	*-16.17%*
Panel I: Including 66-75 year-old	(J_1)	(J_2)	(J_3)	(J_4)
Financial literacy	-0.230**	0.033	0.696***	-0.500***
	[0.107]	[0.124]	[0.181]	[0.167]
%Fin. literacy effect	*-33.90%*	*0.02%*	*23.11%*	*-20.13%*

In *Panel C* of Table 3.4, I present marginal effects and standard errors from bootstrapped multinomial probit regressions, based on 1,000 replications and using sampling weights. The rationale of the exercise is to confirm that my previous estimates are not due to any 'match bias' or inconsistent weighting. The bootstrapped estimates confirm my previous findings, and the effects are very similar, both in terms of significance and magnitude.

In *Panel D* of Table 3.4, I conduct an additional exercise, aiming to cater to any concerns regarding the large differences in financial literacy that exist between countries. I employ a binary 'High financial literacy' (*hereafter* FLH) indicator, which stems from the computation of percentiles of financial literacy for each country separately. Individuals are in the FLH group if their financial-literacy percentile within their country is greater than 50. If their proxy score belongs to a within-country percentile that is less than or equal to 50, they are in the low financial literacy group (hereafter FLL). Hence, any concerns regarding the results being driven by the higher financial literacy scores in particular countries should be mitigated via this exercise. Indeed, the weighted multinomial probit estimates of Panel D confirm that the 'high financial literacy' group within each country is 15.9% less likely to own cryptocurrencies, i.e. 1.5 percentage points less likely with the predicted probability of ownership being 9.3%. The effect is significant at the 5% level. Moreover, individuals in the 'high financial literacy' group in each country are 9.9% more likely not to intend to own cryptocurrencies in the future, and they are 8.4% less likely not to have heard about them.

In *Panel E* of Table 3.4, I use a logarithmic financial literacy measure and estimate weighted multinomial probit regressions. The estimates confirm the robustness of the negative effect of financial literacy on cryptocurrency ownership, and the effect becomes significant at the 1% level. Moreover, the positive effect of financial literacy on the negative disposition to own cryptocurrencies in the future remains and is significant at the 1% level. The magnitudes of both effects are similar to my baseline estimates in Table 3.2. Finally, the negative effect of financial literacy on lack of awareness about cryptocurrencies remains but becomes marginally insignificant at conventional levels.

In *Panels F and G*, I experiment with two alternative financial literacy measures in my weighted multinomial probit regressions. my alternative measure I is computed as $\mathrm{FL}_{\mathrm{i}}^{1} =$

$\prod \frac{FL_{gender} FL_{age} FL_{income}}{FL^2_{country}}$, i.e. as a multiplication of the three financial literacy scores by gender, age and income in each country, and divided with the squared country-level financial literacy score. Then, my alternative measure II removes any country level differences in financial literacy by dividing the multiplicative product of the three scores by the cubed country-level score, i.e. $FL^2_i = \prod \frac{FL_{gender} FL_{age} FL_{income}}{FL^3_{country}}$. Hence, once more, country-level differences are omitted, and my alternative measure II becomes a ranking of the probability for an individual in each country to know at least 3 out of 4 financial-literacy concepts. The effect of an increase of standard deviation in FL^1 (from 0.5304 to 0.7084) on the probability of cryptocurrency ownership is -15.7% and significant at the 5% level. It is 9.87% on having no intention to own cryptocurrencies in the future, and significant at the 1% level. In addition, the effect is in the magnitude of -8.39% on the probability of not having heard about cryptocurrencies. Then, the effect of an increase of one standard deviation in FL^2 (from 1.0527 to 1.2624) on the probability of cryptocurrency ownership is -11.1% and significant at the 1% level. It is 4.99% on the intention not to own cryptocurrencies in the future, and significant at the 1% level. In addition, the effect is in the magnitude of -2.5% on the probability of not having heard about cryptocurrencies, and marginally insignificant.

Finally, *Panels H and I* present weighted multinomial probit estimates for the sub-samples of males and females. The results are robust for the male sub-sample and mostly robust for the female sub-sample. The effect of an increase of one standard deviation (0.1495) in financial literacy on the probability of cryptocurrency ownership is in the magnitude of -46.9% for males. The effect is of a similar magnitude for females, but the marginal effect becomes insignificant at conventional levels for the female sub-sample. This is likely to be due to the fact that both financial literacy and cryptocurrency ownership are lower amongst the female sub-sample. The remaining effects are robust and of higher magnitudes for the male sub-sample, compared to the female sub-sample. Higher financial literacy is positively related to not intending to own cryptocurrencies in the future. The effect is in the magnitude of 30.6% for males and 22.5% for females. Finally, it is confirmed that higher financial literacy is negatively related to lack of awareness about cryptocurrencies. The effect is in the magnitude of -16% for females and marginally insignificant – but of high magnitude – for males.

In the bottom two panels of Table 3.4, I also estimate regressions catering to two additional considerations that are worth a robustness exercise. In *Panel J*, I drop Turkey and Romania from my sample, as these are the countries with particularly high rates of cryptocurrency ownership, and it is worth examining if these are the primary drivers of my main result so far. It is likely that respondents in these countries are more likely to hold cryptocurrencies as assets rather than currencies. The estimates there show that the negative effect of financial literacy on cryptocurrency ownership is significant at the 10% level and of a magnitude of -21.25%. Hence, although the magnitude of the effect is lower, the negative effect is still robust. The positive effect of financial literacy on the intension not to own cryptocurrency in the future remains significant at the 1% level and is of a 15.1% magnitude. The financially literate in the remaining sample are -16.2% less likely not to have heard of cryptocurrencies. Finally, in *Panel I*, I include those aged 66-75, who were dropped in my main sample, for reasons of comparability with the OECD survey and in order to keep the working age population. All effects previously estimated are robust and of high magnitudes, although somewhat smaller than those of Table 3.2.

3.4.3 Selection bias

Another major concern regarding the robustness of my primary findings could stem from the structure of the categorical responses in my variable for attitudes to cryptocurrencies. These also include the individuals who have never heard of cryptocurrencies before, as the fourth response category. In *Table 3.5*, I implement a two-stage methodology, presenting marginal effects from a multinomial probit model with three categories and a 1st stage selection equation[37]. The estimates are weighted, and robust standard errors are shown in brackets. At the first stage, I estimate the probability of having heard about cryptocurrencies, and then, at my 2nd stage, I distinguish between owning, expecting to own in the future, and not expecting to own in the future. As an exclusion restriction in my 1st stage selection equation, I include an additional variable capturing ignorance regarding online payment methods. The wording of the original question was: "*Would you be willing to use any of these providers to pay for goods and services 6 months from now, either in store or online? Please select all the payment methods you would use*" Multiple responses were allowed, involving (i) 'In store'; (ii) 'Online'; (iii) 'I would never use this', and; (iv) 'I don't know this service'. The exclusion restriction captures the lack of awareness of the following main providers, as options to pay for goods and services in the near future, either in store or online:

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[37] The multinomial probit model with a selection equation is estimated using the cmp routine in Stata. The Geweke-Hajivassiliou-Keane algorithm is used for simulating the cumulative multivariate normal distribution (Cappellari and Jenkins 2003; 2005; Gates 2006).

ApplePay, Google/AndroidPay, PayPal, Facebook, AmazonPay (Amazon account), own bank's app. It is a continuous index, ranging from 0 to 1 and stemming from the division of the summation of the 6 dummy variables on unawareness regarding each of the 6 providers – i.e. responses stating that 'I don't know this service' – divided by 6. The additional summary statistics in the *Appendix Table A4* indicate the average score on lack of awareness of online payment providers is 0.282, and that score is higher among individuals with low financial literacy.

Table 3.5
Weighted multinomial probit model with selection

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression with a first stage selection equation modelling the probability of having heard of cryptocurrencies before. Marginal effects for the three categories of the variable on attitudes to cryptocurrencies (Owning; Intending to own in the future, and; Not intending to own in the future) are presented, along with robust standard errors in brackets. The specification is identical to Table 3.2 and includes a constant term. The selection equation is identified via an exclusion restriction capturing ignorance of online payments, in terms of knowledge of the following providers, as options to pay for goods and services in the near future, either in store or online: ApplePay, Google/AndroidPay, PayPal, Facebook, AmazonPay (Amazon account), and own bank's app. It is a continuous index, ranging between 0 and 1, and stemming from the summation of unawareness of the six providers, divided by 6.

	Own	***Intend to own***	***Not intend to own***	**Selection equation: Having heard of**
	(A_1)	(A_2)	(A_3)	(S_1)
Financial literacy	-0.404***	-0.101	0.253**	0.487***
	[0.099]	[0.104]	[0.105]	[0.173]
Digital literacy	0.026**	0.024**	-0.123***	0.151***
	[0.010]	[0.011]	[0.011]	[0.019]
Inflectional FTR	-0.038**	0.069***	-0.063***	0.059**
	[0.016]	[0.019]	[0.019]	[0.024]
Preference for cash	0.020***	0.013**	-0.017***	-0.031***
	[0.005]	[0.005]	[0.005]	[0.008]
Male	-0.023***	-0.044***	-0.026***	0.185***
	[0.005]	[0.006]	[0.006]	[0.009]
Log(Household income per capita)	0.025	0.033**	-0.014	-0.091***
	[0.015]	[0.016]	[0.017]	[0.026]
Log(Household income per capita)^2	-0.008**	-0.009**	0.004	0.028***
	[0.004]	[0.004]	[0.005]	[0.007]
Log(Household income per capita)^3	0.001**	0.001*	-0.001	-0.002***
	[0.000]	[0.000]	[0.000]	[0.001]
Missing household income per capita	-0.021	-0.004	0.035*	-0.022
	[0.018]	[0.018]	[0.019]	[0.027]
Lack of awareness regarding online payment providers	–	–	–	-0.173***
				[0.013]
Predicted probability	0.2258	0.2602	0.4515	0.6590
%Fin. literacy effect	*-23.23%*	*-7.34%*	*7.82%*	*10.17%*
#Observations			13,267	
Log-likelihood			-14,460.6	
Wald χ^2			2,695.8***	

In Table 3.5, I present my estimates from the multinomial probit model with selection. The estimates confirm the robustness of the findings in my baseline model, which did not account for selection. Greater familiarity with online payment methods is positively related to having heard of cryptocurrencies. So is financial literacy in my selection equation, but the effect is of a smaller magnitude, compared to my model in Table 3.2. An increase in financial literacy by one standard deviation increases the probability of having heard of cryptocurrencies by 10.17% and the effect is significant at the 1% level. At the 2nd stage estimates, an increase in financial literacy by one standard deviation (i.e. by 0.1470 from the average of 0.5133) reduces the probability of cryptocurrency ownership by 23.23%. The effect is significant at the 1% level. The one standard deviation increase in financial literacy increases the probability of not intending to own in the future by 7.8%. That effect is significant at the 5% level. Hence, the estimates from the weighted multinomial probit model with selection confirm and further reinforce the robustness of my baseline findings from Table 3.2.

3.4.4 Endogeneity

Another major concern regarding the validity of my estimates could stem from considerations regarding omitted variables confounding my estimates. For instance, one might think that the more financially literate are better able to access conventional assets such as stocks and shares or dollar-denominated bank accounts. Lower levels of financial literacy may be correlated with a lack of access to financial services (Cole, *et al.*, 2011), making cryptocurrencies more attractive. An alternative source of endogeneity could involve any measurement error arising from the fact that my financial literacy variable is a proxy from an external data source. If actual financial literacy is higher than the proxy, my estimates would be biased downwards and that would be less of a concern. However, if actual financial literacy is lower, then my estimates could be biased upwards. In order to cater to these concerns, I estimate instrumental-variable (IV) multinomial probit regressions. my first stage regression estimates financial literacy using an instrument from an additional question in the ING survey. Respondents are asked about their motivation for using mobile banking. One of the response options involved using mobile banking for efficient personal financial management. Intuitively, individuals who give this response can be thought of as more financially literate, and the variable can be thought to be unrelated to the unobserved determinants of attitudes to cryptocurrencies. In the bottom of *Table 3.6*, the tests of my instrumental variable – which stem from a linear probability model of cryptocurrency ownership (available upon request) – confirm the statistical validity of the instrument chosen.

Table 3.6

Weighted instrumental-variables multinomial probit model

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression with a first stage equation modelling endogenous financial literacy. Marginal effects for the for categories of the variable on attitudes to cryptocurrencies (Owning; Intending to own in the future, Not intending to own in the future, and Not having heard of) are presented, along with robust standard errors in brackets. The specification is identical to Table 3.2 and includes a constant term. The first-stage equation is identified via an instrumental variable capturing individuals who responded that they use mobile banking for effective personal financial management in a related question. The additional statistics for instrument validity presented at the bottom of the table are based on a linear probability IV model for cryptocurrency ownership, as the IV multinomial probit model does not allow for the computation of these statistics. Hence, there are presented in a complementary fashion to the main model, to support my argument regarding the validity of my instrument.

	Own	*Intend to own*	*Not intend to own*	*Not having heard of*	**First-stage equation:** *Financial literacy*
	(A_1)	(A_2)	(A_3)	(A_4)	(F_1)
Financial literacy	-0.508***	0.297***	1.004***	-1.058***	–
	[0.009]	[0.006]	[0.008]	[0.008]	
Digital literacy	0.133***	0.178***	-0.031	-0.170***	0.002*
	[0.017]	[0.015]	[0.021]	[0.020]	[0.001]
Inflectional FTR	-0.030	0.138***	-0.049*	-0.043*	-0.003***
	[0.027]	[0.026]	[0.029]	[0.025]	[0.001]
Preference for cash	0.023***	0.005	-0.039***	0.026***	0.001
	[0.008]	[0.007]	[0.009]	[0.009]	[0.000]
Male	0.054***	0.063***	0.097***	-0.181***	0.030***
	[0.007]	[0.007]	[0.009]	[0.008]	[0.000]
Log(Household income)	0.003	-0.011	-0.085***	0.098***	-0.007***
	[0.025]	[0.022]	[0.030]	[0.028]	[0.001]
Log(Household income)^2	-0.002	0.005	0.026***	-0.030***	0.001*
	[0.007]	[0.006]	[0.008]	[0.008]	[0.000]
Log(Household income)^3	0.001	-0.001	-0.002***	0.002***	0.000***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
Missing household income	-0.048	-0.04	0.006	0.045	0.028***
	[0.029]	[0.024]	[0.031]	[0.028]	[0.001]
Mobile banking usage for efficient personal financial management	–	–	–	–	0.001***
					[0.000]
Predicted probability	0.1464	0.1663	0.4651	0.3541	0.5137
%Fin. literacy effect	*-41.27%*	*17.86%*	*29.30%*	*-37.05%*	–

Additional statistics based on a linear probability IV model for cryptocurrency ownership (available upon request)

Test of excluded instruments $F_{(1, 13,225)}$	7.88***	(c) Anderson-Rubin Wald test: $F_{(2,1050)}$	0.42
(a) Kleibergen-Paap rk LM statistic $\chi^2_{(2)}$	7.90***	(c) Anderson-Rubin Wald test: $\chi^2_{(2)}$	0.42
(a) Kleibergen-Paap rk Wald statistic $\chi^2_{(2)}$	7.91***	(c) Stock-Wright LM S-statistic: $\chi^2_{(2)}$	0.42
(b) Kleibergen-Paap Wald rk F-statistic	7.88	(d) Hansen J statistic $\chi2(1)$	0.000

#Observations	13,267
Log-likelihood	17,307.0
Wald χ^2	2,695.8***

The IV multinomial probit regressions confirm the robustness of my findings. The effect of financial literacy on the probability of owning cryptocurrencies is -41.27% and significant at the 1% level. The effect of the probability of not having heard of cryptocurrencies is -37.1% and significant at the 1% level. The one finding that is different is that there is a positive and significant effect of financial literacy on both the positive and the negative inclination to own cryptocurrencies in the future. The effect on the positive inclination is 17.86% and that on the negative inclination is 29.3%. Noting that the effect on the negative inclination is higher, the IV estimates in Table 3.6 confirm the robustness of my previous estimates to endogeneity concerns.

3.4.5 External validity

The biggest concern that might remain, despite the battery of previous robustness exercises, stems from the fact that my financial literacy proxy is derived from an external data source, i.e. from the merging of the S&P financial literacy statistics to the ING database. I have already shown bootstrapped estimates and IV regressions catering to relevant considerations. In this sub-section, I examine the external validity of my results using a completely different sample. Ideally, such a sample incorporates micro-data on financial literacy questions and attitudes towards cryptocurrencies. The OECD 2019 Consumer Insights Survey on Cryptoassets inquired about both, including 2 questions on similar concepts to the S&P survey, capturing the understanding of respondents on financial risk and inflation. Hence, in the new sample, my financial literacy variable is calculated as the number of correct response in the following two questions: "*An investment with a high return is likely to be high risk*", and "*High inflation means that the cost of living is increasing rapidly*". The response categories involved "True", "False", and "I don't know". Noting that this is a sample of retail investors and consumers in 3 countries, who I expect to be more financially literate, 69.9% of respondents answered correctly to both questions, with the figures being 82% on the risk question and 80.3% on the inflation question.

In *Table 3.7*, I present my multinomial probit estimates for attitudes to cryptocurrencies among retail investors in the OECD survey. It is worth noting that the 4 response categories have two different categories, compared to the ING survey, due to the different formatting of the questions. Specifically, the four response categories here are: (i) Currently owning; (ii) Previously held; (iii) Never held; and, (iv) Never heard of. Marginal effects and robust standard errors are presented in brackets. The specification includes a very rich set of control variables, similar to the specifications using the ING survey. Notably, there are questions on digital literacy, risk tolerance, and present orientation, which are used. These variables come from the following questions: "To what extent do the following statements describe you?". "*I am prepared to risk some of my own money when saving or making an investment*" (risk tolerance); "*I tend to live for today and let tomorrow take care of itself*" (present orientation); "*I enjoy learning about new ways of using technology such as smart phones*" (digital literacy). The response categories are: 1 (*Does not describe me very well*); 2 (*Describes me somewhat*); 3 (*Describes me very well*). Apart from these controls, I include control variables for gender (male). Age (5 categories), a 3rd order polynomial in PPP-divided household income, home ownership, education (5 categories), occupation (8 categories), and 3 country dummy variables.

Table 3.7

External validity: Estimates from the OECD Consumer Insights Survey on Cryptoassets (2019)

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a multinomial probit regression. Marginal effects for the for categories of the variable on attitudes to cryptocurrencies (Currently owning; Previously owning; Never held; and, Never heard of) are presented, along with robust standard errors in brackets. The specification includes control variables for labor market status (8 dummies) and a constant term.

	Currently hold	**Previously held**	**Never held**	**Never heard of**
	(1)	(2)	(3)	(4)
Financial literacy	0.002	-0.001	0.034***	-0.034***
	[0.013]	[0.010]	[0.013]	[0.009]
Digital literacy	0.014	-0.011	0.023*	-0.026***
	[0.014]	[0.011]	[0.014]	[0.010]
Risk tolerance	0.112***	-0.013	-0.090***	-0.008
	[0.011]	[0.009]	[0.011]	[0.009]
Present orientation	0.043***	-0.003	-0.078***	0.038***
	[0.010]	[0.008]	[0.010]	[0.008]
Male	0.018	0.015	-0.015	-0.017
	[0.015]	[0.012]	[0.015]	[0.012]
Age: 18-25	0.201***	-0.043	-0.190***	0.033
	[0.048]	[0.036]	[0.043]	[0.036]
–”–: 26-35	0.208***	-0.018	-0.211***	0.021
	[0.045]	[0.033]	[0.040]	[0.034]
–”–: 36-45	0.160***	-0.039	-0.133***	0.012
	[0.045]	[0.033]	[0.040]	[0.034]
–”–: 46-55	0.148***	-0.064*	-0.094**	0.01
	[0.046]	[0.034]	[0.040]	[0.035]
–”–: 56-65	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Log(Household income-PPP)	-0.228***	0.006	0.058	0.164***
	[0.065]	[0.050]	[0.064]	[0.042]
Log(Household income-PPP)^2	0.057***	-0.001	-0.013	-0.045***
	[0.016]	[0.012]	[0.016]	[0.010]
Log(Household income-PPP)^3	-0.003***	0.001	0.001	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]
Home owner	0.142***	0.029**	-0.108***	-0.063***
	[0.017]	[0.014]	[0.017]	[0.013]
Education: No qualifications	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
–”–: Pre-sixteen	-0.133**	-0.042	0.198***	-0.023
	[0.062]	[0.046]	[0.064]	[0.035]
–”–: A-levels, GNVQ or college	-0.132**	-0.101**	0.289***	-0.055
	[0.066]	[0.050]	[0.066]	[0.037]
–”–: University (Bachelor)	-0.051	-0.046	0.234***	-0.137***
	[0.061]	[0.046]	[0.064]	[0.035]
–”–: Higher university degree	-0.014	-0.069	0.200***	-0.117***
	[0.064]	[0.049]	[0.067]	[0.040]
Philippines	0.186***	-0.002	-0.163***	-0.02
	[0.021]	[0.017]	[0.021]	[0.017]
Vietnam	0.043**	0.025*	-0.098***	0.030**
	[0.019]	[0.015]	[0.018]	[0.015]
Predicted probability	0.3688	0.1457	0.3109	0.1746
%Fin. literacy effect	*0.56%*	*-0.90%*	*10.83%*	*-19.73%*
#Observations	3,428			
Log-likelihood	-3,815.6			
Wald χ^2	1,093.7***			

The results in Table 3.7 show a positive effect of financial literacy on the probability of having never held cryptocurrencies. The effect is in the magnitude of 10.83% and significant at the 1% level. The financially literate are also found to be 19.7% less likely to have never heard about cryptocurrencies. These results seem to largely confirm the external validity of my inferences from the ING sample when using the OECD sample. However, it is important to note that since the financial literacy variable in the OECD dataset stems from questions asked of respondents, the potential concern regarding endogeneity from omitted variables might still hold for this sample. Measurement error in the financial literacy variable should be less of a concern in this instance.

Hence, in *Table 3.8*, I present estimates from IV multinomial probit regressions for the OECD sample. my instrument stems from reactions to the following statement: "*I prefer to use financial companies that have a strong ethical stance*". Again, the response categories ranges involved the following 3 categories: 1 (*Does not describe very well*); 2 (*Describes me somewhat*); 3 (*Describes me very well*). Intuitively, one can think of investors interested in ethical finance to be more sophisticated and/or informed. That variable seems unlikely to be correlated with the unobserved determinants of attitudes to cryptocurrencies. The statistics based on a linear probability model for cryptocurrency ownership (available upon request), shown at the bottom of Table 3.8, confirm the validity of my instrument. Moreover, the estimates of Table 3.8 show that financially literate investors are 40.6% less likely to currently hold cryptocurrencies. The magnitude of the effect is very similar to that in my previous ING sample. Moreover, they are 70.5% more likely not to have held cryptocurrencies before, and much less likely never to have heard about cryptocurrencies. Thus, in Tables 3.7 and 3.8 the external validity of my results from the ING sample with the financial literacy proxy are confirmed in the OECD sample, which involved own questions on financial literacy to the respondents.

Table 3.8

External validity: IV estimates from the OECD Consumer Insights Survey on Cryptoassets (2019)

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a instrumental-variable multinomial probit regression. Marginal effects for the for categories of the variable on attitudes to cryptocurrencies (Currently owning; Previously owning; Never held; and, Never heard of) are presented, along with robust standard errors in brackets. The specification includes control variables for age group (5 dummies), labour market status (8 dummies), country (Malaysia, Philippines, and Vietnam) and a constant term. The additional statistics for instrument validity presented at the bottom of the table are based on a linear probability IV model for cryptocurrency ownership, as the IV multinomial probit model does not allow for the computation of these statistics. Hence, there are presented in a complementary fashion to the main model, to support my argument regarding the validity of my instrument.

	Currently hold	**Previously held**	**Never held**	**Never heard of**	**First-stage equation:** ***Financial literacy***
	(A1)	(A2)	(A3)	(A4)	(F1)
Financial literacy	-0.165**	0.034	0.325***	-0.140***	–
	[0.067]	[0.083]	[0.070]	[0.025]	
Preference for ethical finance	–	–	–	–	0.091***
					[0.017]
Digital literacy	0.039*	-0.018	-0.029	-0.001	0.164***
	[0.020]	[0.024]	[0.022]	[0.007]	[0.021]
Risk tolerance	0.116***	0.025**	-0.045***	-0.023***	0.012
	[0.012]	[0.011]	[0.012]	[0.005]	[0.016]
Present orientation	0.049***	0.016	-0.044***	0.004	-0.030**
	[0.012]	[0.012]	[0.014]	[0.005]	[0.013]
Male	0.012	0.024*	-0.01	-0.009	-0.004
	[0.016]	[0.014]	[0.015]	[0.006]	[0.021]
Log(Household income-PPP)	-0.206***	-0.079	-0.010	0.104***	-0.016
	[0.065]	[0.059]	[0.061]	[0.024]	[0.087]
Log(Household income-PPP)^2	0.054***	0.022	-0.002	-0.027***	0.019
	[0.016]	[0.015]	[0.015]	[0.006]	[0.021]
Log(Household income-PPP)^3	-0.003***	-0.001	0.001	0.002***	-0.001
	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
Home owner	0.139***	0.087***	-0.075***	-0.047***	0.060**
	[0.017]	[0.017]	[0.017]	[0.007]	[0.024]
Education: No qualifications	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
–"–: Pre-sixteen	-0.117*	-0.102*	0.105	0.019	0.119
	[0.066]	[0.056]	[0.064]	[0.021]	[0.099]
–"–: A-levels, GNVQ or college	-0.113	-0.177***	0.184**	0.009	0.147
	[0.071]	[0.063]	[0.074]	[0.023]	[0.102]
–"–: University (Bachelor)	-0.032	-0.083	0.117	-0.031	0.254***
	[0.070]	[0.066]	[0.075]	[0.023]	[0.098]
–"–: Higher university degree	-0.009	-0.093	0.140*	-0.036	0.122
	[0.069]	[0.062]	[0.072]	[0.023]	[0.102]
Marginal effect	*-40.58%*	*16.28%*	*70.49%*	*-105.88%*	
Predicted probability	0.4060	0.2104	0.4604	0.1324	1.6237

Statistics based on a linear probability IV model for cryptocurrency ownership (available upon request)			
Test of excluded instruments $F_{(1, 13,225)}$	28.88***	(c) Anderson-Rubin Wald test: $F_{(1, 3,401)}$	0.01
(a) Kleibergen-Paap rk LM statistic $\chi^2_{(2)}$	28.38***	(c) Anderson-Rubin Wald test: $\chi^2_{(2)}$	0.01
(a) Kleibergen-Paap rk Wald statistic $\chi^2_{(2)}$	29.11***	(c) Stock-Wright LM S-statistic: $\chi^2_{(2)}$	0.01
(b) Kleibergen-Paap Wald rk F-statistic	28.88***	(d) Hansen J statistic $\chi2(1)$	0.000

#Observations	3,428
Log-likelihood	-6,800.0
Wald χ^2	4,233.7***

3.5. Moderating factors

In my estimates, I have established that financial literacy is positively related to awareness of cryptocurrencies, negatively related to current ownership of any cryptocurrencies, and positively related to a negative inclination towards future ownership. In this section, I try to identify the mechanics of these relationships in the ING sample, by presenting multinomial probit models, in the context of equation 2. I use the same specification as in Table 3.2 and add interaction terms between financial literacy and some of the key candidate explanations of the relationships I have identified.

3.5.1 Digital literacy, preference for cash, age, and financial advice

In columns A_1-A_4 of *Table 3.9*, I present estimates in which I interact financial literacy with the digital literacy variable. The effects of the interaction terms between financial literacy and digital literacy are small and insignificant at any conventional levels. Moreover, the sign, the magnitude, and the significance of the marginal effects of financial literacy on my 4 categories for attitudes to cryptocurrencies remain largely unaffected, and similar to those presented in Table 3.2.

Table 3.9

Interactions between financial literacy and (i) digital literacy; (ii) preference for cash

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_4 and Columns B_1 - B_4, respectively, along with robust standard errors in brackets. The first model (A_1 - A_4) incorporates an interaction term between financial literacy and digital literacy. The second model (B_1 - B_4) incorporates an interaction term between financial literacy and preference for cash. The remaining specification is identical to that of Table 3.2.

	Own	*Intend to own*	*Not intend to own*	*Not having heard of*	*Own*	*Intend to own*	*Not intend to own*	*Not having heard of*
	(A_1)	(A_2)	(A_3)	(A_4)	(B_1)	(B_2)	(B_3)	(B_4)
Financial literacy	-0.289**	0.063	0.736***	-0.510***	-0.334***	0.021	0.750***	-0.437**
	[0.127]	[0.143]	[0.202]	[0.187]	[0.119]	[0.139]	[0.196]	[0.181]
Digital literacy	0.130***	0.116***	-0.008	-0.237***	0.120***	0.132***	-0.077***	-0.175***
	[0.037]	[0.044]	[0.073]	[0.069]	[0.012]	[0.014]	[0.021]	[0.019]
Financial literacy*Digital literacy	-0.020	0.035	-0.135	0.120	–	–	–	–
	[0.072]	[0.085]	[0.134]	[0.128]				
Preference for cash	0.012**	0.002	-0.042***	0.029***	-0.010	-0.039*	0.012	0.038
	[0.006]	[0.006]	[0.009]	[0.009]	[0.018]	[0.022]	[0.033]	[0.031]
Fin. literacy*Preference for cash	–	–	–	–	0.044	0.083**	-0.107*	-0.019
					[0.035]	[0.042]	[0.061]	[0.058]
Inflectional FTR	-0.008	0.130***	-0.042	-0.080***	-0.008	0.129***	-0.042	-0.079***
	[0.019]	[0.025]	[0.028]	[0.024]	[0.019]	[0.025]	[0.028]	[0.024]
Male	0.067***	0.049***	0.075***	-0.192***	0.067***	0.049***	0.076***	-0.192***
	[0.006]	[0.007]	[0.010]	[0.009]	[0.006]	[0.007]	[0.010]	[0.009]
Log(Household income p.c.)	-0.015	-0.01	-0.076**	0.101***	-0.014	-0.008	-0.080***	0.101***
	[0.018]	[0.020]	[0.030]	[0.026]	[0.018]	[0.020]	[0.030]	[0.026]
Log(Household income p.c.)^2	0.004	0.004	0.023***	-0.030***	0.003	0.003	0.024***	-0.030***
	[0.005]	[0.006]	[0.008]	[0.007]	[0.005]	[0.006]	[0.008]	[0.007]
Log(Household income p.c.)^3	-0.001	-0.001	-0.002***	0.002***	-0.001	-0.001	-0.002***	0.002***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]
Missing household income	-0.039*	-0.019	0.032	0.026	-0.039*	-0.02	0.033	0.026
	[0.021]	[0.023]	[0.032]	[0.027]	[0.021]	[0.023]	[0.032]	[0.027]
%Fin. literacy effect	*-38.50%*	*2.25%*	*25.06%*	*-20.92%*	*-42.68%*	*-2.16%*	*25.51%*	*-18.50%*
#Observations	13,267				13,267			
Log-likelihood	-14,574.2				-14,574.2			
Wald χ^2	2,935.4***				2,935.4***			

In columns B_1-B_4 of Table 3.9, I present estimates in which I interact financial literacy with the preference for cash variable. The results confirm that that a higher preference for cash, and potentially informal conduct, does not explain the negative relationship between financial literacy and cryptocurrency ownership. There is a positive effect of the interaction term between financial literacy and preference for cash on the intention to own in the future. Moreover, there is a negative effect of the interaction term on no intention to own in the future. There is also an insignificant marginal effect of the interaction term on the probability of current ownership. These might suggest that my preference for cash variable could be depicting favorable attitudes towards informal practices, and those favoring such practices might be both more financially literate and in favor of cryptocurrency ownership. However, both the magnitudes and the significance of the effects of financial literacy remain. Hence, neither higher financial literacy among the more digitally literate nor lower financial literacy among those favoring informal practices[38] explain why financial literacy is negatively related to cryptocurrency ownership and positively related to the intention not to own cryptocurrency in the future.

In *Table 3.10*, I present marginal effects from multinomial probit estimates, in which I interact financial literacy with age categories. In the specification of columns A_1-A_4, I replace my age dummies with a single dichotomous variable, taking the value one for individuals younger than 45. I also include an interaction term between financial literacy and younger age. Alternatively, the effect could be driven by a non-linear relationship between financial literacy and age, and by older adults being less willing to engage with cryptocurrencies. The correlation matrix of the *Appendix Table A5* confirms a positive weighted pairwise correlation between financial literacy and the continuous age variable. Hence, in the specification of columns B_1-B_4, I replace age with dummy variables for each of my five age groups, namely individuals aged 18-25, 26-35, 36-45, 46-55, and 56-65 (reference category). Moreover, I include five interaction terms between financial literacy and the age dummies. Both sets of estimates confirm the robustness of my findings. Financially literate young adults are more likely to own and intend to own cryptocurrencies, and less likely not to intend to own and not to have heard about cryptocurrencies. However, financial literacy remains negatively related to current ownership and the effect is significant at the 5% level. It remains positively related to no intention to own in the future and negatively related to unawareness about cryptocurrencies. Hence, the higher cryptocurrency ownership and positive disposition towards cryptocurrencies among the more financially literate younger sub-sample is not the primary driver of the effect of financial literacy.

[38] The higher digital literacy and the lower preference for cash by the more financial literate is indicated in the weighted summary statistics by high and low financial literacy group, presented in the *Appendix 1 Table A5*. The is also the case for the higher financial literacy among the younger sub-sample, i.e. those younger than 45.

Table 3.10

Interactions between financial literacy and age

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_4 and Columns B_1 - B_4, respectively, along with robust standard errors in brackets. The first model (A_1 - A_4) incorporates an interaction term between financial literacy and young age (<45). The second model (B_1 - B_4) incorporates five interaction term between financial literacy and six age categories. namely 18-25, 26-35, 36-45, 46-55. 56-65 (reference group). The remaining specification is identical to that of Table 3.2.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***	***Own***	***Intend to own***	***Not intend to own***	***Not having heard of***
	(A_1)	(A_2)	(A_3)	(A_4)	(B_1)	(B_2)	(B_3)	(B_4)
Financial literacy	-0.266**	0.108	0.584***	-0.426**	-0.274**	0.147	0.700***	-0.573***
	[0.116]	[0.134]	[0.188]	[0.174]	[0.123]	[0.144]	[0.200]	[0.184]
Young age (<45)	-0.022	-0.045**	-0.054	0.120***	–	–	–	–
	[0.018]	[0.022]	[0.033]	[0.031]				
Fin. Literacy*Young age	0.128***	0.163***	-0.089	-0.202***	–	–	–	–
	[0.033]	[0.041]	[0.060]	[0.055]				
Age: 18-25	–	–	–	–	-0.074**	-0.037	-0.054	0.164***
					[0.030]	[0.036]	[0.055]	[0.050]
–"– 26-35	–	–	–	–	-0.012	-0.067**	-0.039	0.118**
					[0.027]	[0.033]	[0.050]	[0.047]
–"– 36-45	–	–	–	–	-0.025	-0.032	-0.029	0.086*
					[0.026]	[0.033]	[0.049]	[0.046]
–"– 46-55	–	–	–	–	-0.004	-0.004	0.033	-0.025
					[0.028]	[0.034]	[0.049]	[0.047]
–"– 56-65	–	–	–	–	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
Fin. literacy*Age: 18-25	–	–	–	–	0.283***	0.218***	-0.211**	-0.290***
					[0.056]	[0.067]	[0.099]	[0.092]
Fin. literacy*Age: 26-35	–	–	–	–	0.166***	0.233***	-0.233**	-0.166*
					[0.051]	[0.063]	[0.092]	[0.086]
Fin. literacy*Age: 36-45	–	–	–	–	0.129***	0.113*	-0.139	-0.103
					[0.050]	[0.061]	[0.088]	[0.082]
Fin. literacy*Age: 46-55	–	–	–	–	0.061	0.022	-0.171*	0.088
					[0.053]	[0.065]	[0.090]	[0.085]
Fin. literacy*Age: 56-65	–	–	–	–	{*Ref.*}	{*Ref.*}	{*Ref.*}	{*Ref.*}
Digital literacy	0.123***	0.134***	-0.085***	-0.173***	0.118***	0.131***	-0.077***	-0.172***
	[0.012]	[0.014]	[0.021]	[0.019]	[0.012]	[0.014]	[0.021]	[0.019]
Inflectional FTR	-0.007	0.130***	-0.042	-0.080***	-0.007	0.132***	-0.044	-0.081***
	[0.019]	[0.025]	[0.028]	[0.024]	[0.019]	[0.025]	[0.028]	[0.024]
Preference for cash	0.012**	0.003	-0.043***	0.028***	0.012**	0.003	-0.043***	0.028***
	[0.006]	[0.006]	[0.009]	[0.009]	[0.006]	[0.006]	[0.009]	[0.009]
Male	0.064***	0.046***	0.080***	-0.190***	0.063***	0.044***	0.079***	-0.186***
	[0.006]	[0.007]	[0.010]	[0.009]	[0.006]	[0.007]	[0.010]	[0.009]
%Fin. literacy effect	*-35.87%*	*7.92%*	*19.83%*	*-17.77%*	*-36.85%*	*10.78%*	*23.52%*	*-22.99%*
#Observations	13,267				13,267			
Log-likelihood	-14,586.4				-14,538.4			
Wald χ^2	2,910.6***				2,969.1***			

In *Table 3.11*, I test one additional explanation for the established relationship between financial literacy and attitudes to cryptocurrencies, for the sub-sample of the 8.734 individuals who have heard of cryptocurrencies before. In the estimates of columns A_1-A_3, I depart from the baseline specification and adhere five dummy variables for the sources of financial advice. Then, in columns B_1-B_3, I also adhere the respective interaction terms between financial literacy and different sources of financial advice on investment and cryptocurrencies[39].

[39] I merge the two final categories in one variable − namely (5) I (would) never invest money in cryptocurrency and (6) I don't know – into one category depicting not seeking specific financial advice regarding cryptocurrencies. It is worth noting that my estimates remain unaffected by the merging and that, when used separately, the two variables (and their interaction terms with financial literacy) have almost identical effects on attitudes to cryptocurrencies. These results are available upon request.

Table 3.11

The interactions between financial literacy and sources of financial advice for investment

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions for the sub-sample of individuals who have heard of cryptocurrencies before. Marginal effects for the remaining three categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_3 and Columns B_1 - B_3, respectively, along with robust standard errors in brackets. The first model (A_1 - A_3) incorporates five variables capturing distinctive sources of financial advice on cryptocurrencies among individuals who have heard of them. The second model (B_1 - B_3) also incorporates five interaction terms between financial literacy and the sources of financial advice on cryptocurrencies. The remaining specification is identical to that of Table 3.2.

	Own	***Intend to own***	***Not intend to own***	***Own***	***Intend to own***	***Not intend to own***
	(A_1)	(A_2)	(A_3)	(B_1)	(B_2)	(B_3)
Financial literacy	-0.546***	-0.040	0.586***	-0.515***	-0.104	0.619***
	[0.165]	[0.189]	[0.202]	[0.174]	[0.198]	[0.210]
Fin. advice: Independent financial or bank advisor	0.080***	0.224***	-0.305***	0.068	0.182***	-0.250***
	[0.012]	[0.012]	[0.012]	[0.044]	[0.045]	[0.046]
–"– My friends/family	0.138***	0.225***	-0.363***	0.118**	0.124**	-0.243***
	[0.014]	[0.016]	[0.016]	[0.050]	[0.061]	[0.063]
–"– The internet and specialist websites	0.154***	0.221***	-0.374***	0.211***	0.174***	-0.385***
	[0.010]	[0.011]	[0.010]	[0.038]	[0.041]	[0.042]
–"– An online computer program or algorithm	0.205***	0.245***	-0.450***	0.167***	0.249***	-0.416***
for tailored advice	[0.014]	[0.017]	[0.017]	[0.048]	[0.056]	[0.061]
–"– No financial advice	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Fin. literacy*Fin. advice: An independent	–	–	–	0.027	0.084	-0.111
financial or bank advisor				[0.083]	[0.087]	[0.089]
Fin. literacy*Fin. advice: My friends/family	–	–	–	0.035	0.197*	-0.232**
				[0.093]	[0.113]	[0.117]
Fin. literacy*Fin. advice: The internet and	–	–	–	-0.118*	0.096	0.022
specialist websites				[0.072]	[0.080]	[0.080]
Fin. literacy*Fin. advice: An online computer	–	–	–	0.076	-0.01	-0.066
program or algorithm for tailored advice				[0.091]	[0.110]	[0.118]
Fin. literacy* No financial advice	–	–	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Digital literacy	0.112***	0.080***	-0.192***	0.111***	0.081***	-0.192***
	[0.017]	[0.020]	[0.022]	[0.017]	[0.020]	[0.022]
Inflectional FTR	-0.038	0.190***	-0.152***	-0.04	0.192***	-0.152***
	[0.030]	[0.037]	[0.037]	[0.030]	[0.037]	[0.037]
Preference for cash	0.016**	0.003	-0.020**	0.015*	0.003	-0.019*
	[0.008]	[0.009]	[0.010]	[0.008]	[0.009]	[0.010]
Male	0.058***	0.006	-0.064***	0.057***	0.006	-0.063***
	[0.009]	[0.010]	[0.011]	[0.009]	[0.010]	[0.011]
Log(Household income per capita)	-0.012	0.014	-0.002	-0.013	0.015	-0.002
	[0.026]	[0.030]	[0.033]	[0.026]	[0.030]	[0.033]
Log(Household income per capita)^2	0.001	-0.005	0.004	0.001	-0.005	0.004
	[0.007]	[0.008]	[0.009]	[0.007]	[0.008]	[0.009]
Log(Household income per capita)^3	-0.001	0.001	-0.001	-0.001	0.001	-0.001
	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]
Missing household income per capita	-0.053*	-0.012	0.065*	-0.054*	-0.013	0.067*
	[0.031]	[0.034]	[0.037]	[0.031]	[0.034]	[0.037]
%Fin. literacy effect	*-44.90%*	*-6.60%*	*12.43%*	*-43.35%*	*-10.46%*	*13.23%*
#Observations		8,734			8,734	
Log-likelihood		-6,457.1			-6,448.7	
Wald χ^2		2,079.6***			2,080.0***	

The estimates in columns A_1-A_3 of *Table 3.11* indicate that more sophisticated types of financial advice about cryptocurrencies exert a higher impact on the probability of ownership. Hence, individuals seeking tailored advice via computer programs and algorithms (i.e. robo-advice), as well as advice from the internet and specialist websites are more likely to own cryptocurrencies, compared to those not seeking any advice on cryptocurrencies. This is also the case for individuals seeking advice from friends and family, and from an independent financial or bank advisor. The effect on cryptocurrency ownership of advice from an independent financial or bank advisor is of a smaller magnitude, compared to the effects of the remaining sources of advice. The effects of financial literacy on attitudes to cryptocurrencies remain unaffected by the inclusion of the related financial advice variables in columns A_1-A_3, in all terms of sign, significance and magnitude. The effects of financial literacy become even larger in size, and the negative effect of financial literacy on current ownership becomes significant at the 1% level.

In columns B_1-B_3, I also include interaction terms between financial literacy and the sources of financial advice on cryptocurrencies. Some interesting patterns prevail with respect to the effects of the interaction terms. Financially literate individuals seeking advice from the internet and specialist websites are less likely to own cryptocurrencies. Moreover, financially literate individuals seeking financial advice from friends and family are more likely to intend to own and less likely to have no intention to own in the future. This could be indicative of either a selection of distinctive information sources by the more financially literate or of peer effects stemming from imitation of friends and family. However, once more, the effects of the financial literacy variable remain robust and of similar magnitudes to those of Table 3.2.

3.5.2 *The role of perceptions of reward and risk*

In the previous sub-section, I established that none of the current proposed moderators so far − namely digital literacy, preference for cash/informality, young age, and financial advice – can fully explain the established relationships between financial literacy and attitudes to cryptocurrencies. In this sub-section, I aim to test a fifth moderator, which is compatible with my expectation regarding the role of financial literacy on financial decision making. One would expect the financially literate to be in a better position to evaluate financial risk, and the related relationship between risk and reward. In order to examine this prediction, I interact financial literacy with proxies for the likely reward and risk from engagement with the cryptocurrency market.

In *Table 3.12*, I introduce a set of three cardinal variables capturing the reward prospects of holding cryptocurrencies. I estimate my multinomial probit specification for individuals who have heard of cryptocurrencies before and introduce the three variables, ranging from 1 to 5 (columns A_1-A_3). For each of the three variables, higher values indicate that respondents are more likely to agree that cryptocurrencies are the future of spending online (*consumption motive*), the future of investment as a store of value (*investment motive*), and that the value of cryptocurrencies will increase in the next 12 months (*speculation motive*), respectively. In columns B_1-B_3, I also introduce interaction terms between financial literacy and each of the three reward perception variables. The estimates in columns A_1-A_3 indicate that all three reward perceptions regarding the prospects of cryptocurrencies are positively related to ownership and prospective future ownership. They are also negatively related to not intending to own cryptocurrencies in the future. The inspection of the coefficients suggests that the investment motive has a smaller marginal effect on current ownership, compared to the consumption or speculation motive. Moreover, the speculation motive has a smaller marginal effect on the positive disposition to future ownership, compared to the consumption and investment motive. Finally, the consumption motive exerts a higher negative impact than the investment motive. Then, the investment motive exerts a higher impact than the speculation motive on the negative disposition to future ownership.

Table 3.12

The interactions between financial literacy and the perception of rewards from cryptocurrencies

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions for the sub-sample of individuals who have heard of cryptocurrencies before. Marginal effects for the remaining three categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_3 and Columns B_1 - B_3, respectively, along with robust standard errors in brackets. The first model (A_1 - A_3) incorporates three variables capturing reward perceptions on cryptocurrencies among the individuals who have heard of them. The second model (B_1 - B_3) also incorporates three interaction terms between financial literacy and the reward perceptions on cryptocurrencies. The remaining specification is identical to that of Table 3.2.

	Own	***Intend to own***	***Not intend to own***	***Own***	***Intend to own***	***Not intend to own***
	(A_1)	(A_2)	(A_3)	(B_1)	(B_2)	(B_3)
Financial literacy	-0.498***	0.141	0.357*	-0.456**	0.006	0.450**
	[0.163]	[0.183]	[0.185]	[0.191]	[0.207]	[0.217]
Digital currencies – e.g. bitcoin – are the future of spending online	0.037***	0.053***	-0.091***	0.046***	0.023	-0.069***
	[0.005]	[0.006]	[0.006]	[0.017]	[0.021]	[0.021]
–"– are the future of investment as storage of value	0.024***	0.053***	-0.078***	0.050***	0.057**	-0.106***
	[0.006]	[0.007]	[0.006]	[0.018]	[0.022]	[0.022]
I think the value of digital currencies – e.g. bitcoin – will increase in the next 12 months	0.038***	0.014***	-0.053***	0.011	0.022	-0.033*
	[0.005]	[0.005]	[0.005]	[0.016]	[0.018]	[0.019]
Fin. literacy*Future of spending online	–	–	–	-0.018	0.062	-0.043
				[0.034]	[0.041]	[0.040]
Fin. literacy*Future of investment or storage of value	–	–	–	-0.049	-0.007	0.056
				[0.035]	[0.043]	[0.042]
Fin. literacy*The value will increase in next 12 months	–	–	–	0.054*	-0.014	-0.04
				[0.031]	[0.035]	[0.036]
Digital literacy	0.082***	0.063***	-0.145***	0.082***	0.062***	-0.144***
	[0.017]	[0.019]	[0.020]	[0.017]	[0.020]	[0.020]
Inflectional FTR	-0.071**	0.167***	-0.097***	-0.072**	0.168***	-0.096***
	[0.030]	[0.038]	[0.035]	[0.030]	[0.038]	[0.035]
Preference for cash	0.002	-0.006	0.005	0.002	-0.006	0.004
	[0.008]	[0.009]	[0.009]	[0.008]	[0.009]	[0.009]
Male	0.071***	0.019*	-0.091***	0.071***	0.019*	-0.090***
	[0.009]	[0.010]	[0.010]	[0.009]	[0.010]	[0.010]
Log(Household income per capita)	0.001	0.019	-0.019	-0.001	0.020	-0.019
	[0.025]	[0.029]	[0.030]	[0.025]	[0.029]	[0.030]
Log(Household income per capita)^2	-0.002	-0.006	0.008	-0.001	-0.006	0.008
	[0.007]	[0.008]	[0.008]	[0.007]	[0.008]	[0.008]
Log(Household income per capita)^3	0.001	0.001	-0.001	0.001	0.001	-0.001
	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]
Missing household income per capita	-0.021	-0.015	0.037	-0.021	-0.015	0.036
	[0.030]	[0.033]	[0.034]	[0.030]	[0.033]	[0.034]
%Fin. literacy effect	*-41.72%*	*5.96%*	*7.39%*	*-39.28%*	*-2.59%*	*9.66%*
#Observations		8,734			8,734	
Log-likelihood		-5841.4			-5837.1	
Wald χ^2		2,143.0***			2,139.1***	

The estimates in columns B_1-B_3 indicate that the interaction terms between financial literacy and the three reward perceptions on cryptocurrencies exert insignificant impacts on all three attitudes to cryptocurrencies. The effect of financial literacy becomes significant at the 5% level and has a similar magnitude to my baseline model in Table 3.2. The positive effect on having no intention to own cryptocurrencies in the future is significant at the 5% level. Hence, different perceptions regarding the prospective rewards of engagement in cryptocurrencies by the financially literate are not the main moderating factor for the effects of financial literacy on attitudes to cryptocurrencies.

In *Table 3.13*, I introduce a set of six cardinal variables capturing the perceptions of the risk involved in investment in cryptocurrencies compared to six alternative assets, namely cash, bonds, stocks, real estate/property funds, gold, and investment in one's own business. I estimate my multinomial probit specification for individuals who have heard of cryptocurrencies before and introduce the six variables, which range between 1 and 5 (columns A_1-A_3). For each of the six variables, higher values indicate that respondents believe that holding cryptocurrencies entails more risk than holding each of the six alternative assets, respectively. In columns B_1-B_3, I also introduce interaction terms between financial literacy and each of the six risk perception variables. The estimates in columns A_1-A_3 indicate that respondents who believe that cryptocurrencies are riskier than cash, bonds, stocks, and investment in own business are less likely to own cryptocurrencies. Believing that cryptocurrencies are riskier than cash, bonds, stocks and entrepreneurship exerts negative impacts on current ownership. Moreover, believing that cryptocurrencies are riskier than cash, stocks and entrepreneurship exerts negative impacts on and the intention to own in the future. These same variables of comparative assessment of risk exert positive impacts on the intention not to own in the future. Believing that cryptocurrencies are riskier than gold exerts a positive impact on the intension to own in the future.

Table 3.13

The interaction between financial literacy and risk perception

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions for the sub-sample of individuals who have heard of cryptocurrencies before. Marginal effects for the remaining three categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_3 and Columns B_1 - B_3, respectively, along with robust standard errors in brackets. The first model (A_1 - A_3) incorporates six variables capturing risk perceptions on cryptocurrencies among the individuals who have heard of them. The second model (B_1 - B_3) also incorporates six interaction terms between financial literacy and risk perception of cryptocurrencies. The remaining specification is identical to that of Table 3.2.

	Own	*Intend to own*	*Not intend to own*	*Own*	*Intend to own*	*Not intend to own*
	(A_1)	(A_2)	(A_3)	(B_1)	(B_2)	(B_3)
Financial literacy	-0.473***	0.076	0.397*	-0.307*	0.156	0.151
	[0.168]	[0.193]	[0.214]	[0.185]	[0.218]	[0.245]
Cryptocurrency riskier than cash	-0.007*	-0.013***	0.020***	-0.008	0.002	0.006
	[0.004]	[0.004]	[0.005]	[0.012]	[0.015]	[0.017]
- ” - bonds	-0.010**	0.001	0.008	-0.007	-0.001	0.008
	[0.004]	[0.005]	[0.005]	[0.013]	[0.015]	[0.017]
- ” - stocks	-0.012***	-0.033***	0.045***	-0.030***	-0.022	0.052***
	[0.004]	[0.004]	[0.005]	[0.012]	[0.014]	[0.016]
- ” - real estate/property funds	-0.002	0.001	0.001	0.034***	-0.011	-0.023
	[0.004]	[0.005]	[0.005]	[0.013]	[0.016]	[0.018]
- ” - gold	-0.006	0.009*	-0.003	0.02	0.006	-0.026
	[0.004]	[0.005]	[0.005]	[0.013]	[0.016]	[0.018]
- ” - investing in own business	-0.008**	-0.013***	0.021***	-0.035***	-0.009	0.044***
	[0.004]	[0.004]	[0.005]	[0.012]	[0.014]	[0.016]
Fin. literacy* Crypto. riskier than cash	–	–	–	0.004	-0.031	0.027
				[0.023]	[0.029]	[0.032]
- ” - bonds	–	–	–	-0.005	0.005	-0.001
				[0.025]	[0.030]	[0.034]
- ” - stocks	–	–	–	0.038*	-0.023	-0.015
				[0.023]	[0.028]	[0.031]
- ” - real estate/property funds	–	–	–	-0.073***	0.027	0.046
				[0.025]	[0.031]	[0.034]
- ” - gold	–	–	–	-0.051**	0.006	0.045
				[0.025]	[0.031]	[0.035]
- ” - investing in own business	–	–	–	0.054**	-0.009	-0.045
				[0.023]	[0.028]	[0.031]
Digital literacy	0.134***	0.134***	-0.268***	0.134***	0.134***	-0.268***
	[0.017]	[0.020]	[0.023]	[0.017]	[0.020]	[0.023]
Inflectional FTR	-0.047	0.191***	-0.144***	-0.048	0.191***	-0.144***
	[0.030]	[0.039]	[0.039]	[0.030]	[0.039]	[0.039]
Preference for cash	0.016*	0.007	-0.023**	0.014*	0.008	-0.022**
	[0.008]	[0.009]	[0.011]	[0.008]	[0.009]	[0.011]
Male	0.070***	0.017	-0.087***	0.070***	0.017	-0.086***
	[0.009]	[0.011]	[0.012]	[0.009]	[0.011]	[0.012]
%Fin. literacy effect	*-40.34%*	*2.47%*	*8.25%*	*-28.46%*	*9.42%*	*2.96%*
#Observations		8,734			8,734	
Log-likelihood		-6,955.7			-6,941.1	
Wald χ^2		1,411.0***			1,460.4***	

The estimates in columns B_1-B_3, in which interaction terms between financial literacy and the six risk perceptions are introduced in the specification, reveal some interesting patterns. Firstly, there are significant negative interaction effects on the probability of owning cryptocurrency. These are the effects of the interaction terms between financial literacy and the perception that cryptocurrencies are riskier than real estate/property funds, and between financial literacy and the perception that they are riskier than gold. There is a positive effect on the probability of owning cryptocurrencies by the interaction term between financial literacy and the perception that cryptocurrencies are riskier than an investment in one's own business and in stocks. Hence, the financially literate individuals who believe that cryptocurrencies are riskier than real estate and gold are less likely to own cryptocurrencies at present. This is likely to indicate a greater ability by the more financially literate to assess the objective risk of cryptocurrencies, in comparison to these alternative assets which entail the highest risk among the options offered. Financially literate respondents who believe that cryptocurrencies entail more risk than stocks and entrepreneurship, are more likely to own cryptocurrencies. The latter is a rather odd finding, which could be driven by the highest cryptocurrency ownership among the self-employed or by the fact that entrepreneurship might entail an innate ability (Baumol, 1990) and is not really seen as an alternative asset by the non-entrepreneurial population. Secondly, in the specification with the interaction terms of columns B_1-B_3, the effect of financial literacy on attitudes to cryptocurrencies becomes lower in terms of magnitude and it becomes insignificant in all columns. Hence, it appears that the negative effect of financial literacy on cryptocurrency ownership and the positive effect on the intention not to own cryptocurrency in the future are likely to be driven by the different assessments of the risk of cryptocurrencies, compared to alternative assets, by the more financially literate. This is in accordance with my prior expectation that the ability to assess financial risk is a key financial literacy skill.

In *Table 3.14*, I introduce both sets of reward and risk perceptions regarding cryptocurrencies (columns A_1-A_3), and then, the interaction terms between financial literacy and the 3 reward variables and the 6 risk variables (columns B_1-B_3). The estimation results in columns A_1-A_3 are identical to those of the respective columns of Table 3.12 and 3.13. The effects of financial literacy on attitudes to cryptocurrencies remains significant and similar to those of my baseline specification in Table 3.2. In the models with the nine interaction terms in columns B_1-B_3, the magnitude of the effect of financial literacy diminishes to less than half and becomes insignificant at conventional levels. This confirms and further reinforces the findings of the previous Table 3.13.

After all, the ability to understand financial risk should correlate with understanding financial reward, as well as an understanding of the relationship between financial risk and reward.

Table 3.14

The interaction between financial literacy and perceptions of reward and risk

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions for the sub-sample of individuals who have heard of cryptocurrencies before. Marginal effects and robust standard errors are presented in brackets. The first model (A_1 - A_3) incorporates nice variables capturing reward and risk perceptions on cryptocurrencies among the individuals who have heard of them. The second model (B_1 - B_3) also incorporates nine interaction terms between financial literacy and risk perception of cryptocurrencies. The remaining specification is identical to that of Table 3.2.

	Own	*Intend to own*	*Not intend to own*	*Own*	*Intend to own*	*Not intend to own*
	(A_1)	(A_2)	(A_3)	(B_1)	(B_2)	(B_3)
Financial literacy	-0.489***	0.133	0.356*	-0.202	0.011	0.191
	[0.162]	[0.183]	[0.184]	[0.232]	[0.252]	[0.269]
Digital currencies – e.g. bitcoin – are the future of	0.036***	0.053***	-0.089***	0.048***	0.019	-0.067***
spending online	[0.005]	[0.006]	[0.006]	[0.018]	[0.021]	[0.022]
–”– are the future of investment as storage of value	0.023***	0.053***	-0.076***	0.052***	0.061***	-0.113***
	[0.006]	[0.007]	[0.006]	[0.019]	[0.022]	[0.022]
I think the value of digital currencies – e.g. bitcoin	0.038***	0.014***	-0.052***	0.013	0.021	-0.034*
– will increase in the next 12 months	[0.005]	[0.005]	[0.005]	[0.016]	[0.018]	[0.019]
Fin. literacy*Future of spending online	–	–	–	-0.026	0.069*	-0.044
				[0.034]	[0.041]	[0.041]
Fin. literacy*Future of investment or storage of value	–	–	–	-0.057	-0.015	0.071*
				[0.035]	[0.043]	[0.042]
Fin. literacy*The value will increase in next 12 months	–	–	–	0.049	-0.014	-0.035
				[0.031]	[0.035]	[0.035]
Fin. literacy* Cryptocurrency riskier than cash	0.001	-0.004	0.004	-0.003	0.006	-0.003
	[0.003]	[0.004]	[0.004]	[0.011]	[0.013]	[0.014]
- ” - bonds	-0.004	0.007	-0.003	0.001	0.01	-0.011
	[0.004]	[0.004]	[0.005]	[0.012]	[0.014]	[0.015]
- ” - stocks	0.001	-0.017***	0.016***	-0.017	-0.011	0.029**
	[0.003]	[0.004]	[0.004]	[0.011]	[0.013]	[0.014]
- ” - real estate/property funds	0.002	0.005	-0.007	0.032***	-0.015	-0.017
	[0.004]	[0.004]	[0.005]	[0.012]	[0.015]	[0.016]
- ” - gold	-0.003	0.012***	-0.008*	0.022*	0.011	-0.033**
	[0.004]	[0.004]	[0.005]	[0.012]	[0.015]	[0.016]
- ” - investing in own business	-0.002	-0.004	0.006	-0.022*	0.002	0.02
	[0.004]	[0.004]	[0.004]	[0.011]	[0.013]	[0.014]
Fin. literacy* Cryptocurrency riskier than cash	–	–	–	0.006	-0.02	0.014
				[0.022]	[0.026]	[0.028]
- ” - bonds	–	–	–	-0.011	-0.006	0.017
				[0.023]	[0.028]	[0.029]
- ” - stocks	–	–	–	0.036	-0.011	-0.024
				[0.022]	[0.026]	[0.027]
- ” - real estate/funds	–	–	–	-0.061***	0.043	0.017
				[0.023]	[0.029]	[0.030]
- ” - gold	–	–	–	-0.050**	0.002	0.048
				[0.023]	[0.029]	[0.030]
- ” - investing in own business	–	–	–	0.041*	-0.013	-0.028
				[0.022]	[0.025]	[0.027]
%Fin. literacy effect	*-41.15%*	*5.53%*	*7.39%*	*-19.67%*	*0.07%*	*4.24%*
#Observations		8,734			8,734	
Log-likelihood		-5,821.9			-5,804.1	
Wald χ^2		2,159.7***			2,189.1***	

In *Table 3.15*, I introduce a set of variables for perceptions of reward and risk, which are continuous transformations of the respective sets of variables used in the previous tables. Specifically, in columns A_1-A_3, I introduce a reward perception variable, which stems from the summation of the 3 reward variables, divided by 15, i.e. $Reward\ perception = \sum_{i=1}^{3} \frac{Reward_i}{15}$. The risk perception variable is the summation of the 6 risk variables, divided by 30, i.e. $Risk\ perception = \sum_{i=1}^{6} \frac{Risk_i}{30}$. Then, in columns B_1-B_3, I also introduce two interaction terms, one between financial literacy and the continuous reward variable, and another between financial literacy and the continuous risk variable. The results in columns A_1-A_3 confirm that the reward perception exerts a large positive impact on cryptocurrency ownership and prospective ownership in the future. It exerts a large negative impact on the intention not to own cryptocurrency in the future. The risk perception variable exerts a smaller negative impact on the probability of cryptocurrency ownership. It is significant at the 10% level. The effects of financial literacy remain significant and of magnitudes similar to those of my baseline specification in Table 3.2.

Table 3.15
The interaction between financial literacy and continuous reward/risk variables

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from two weighted multinomial probit regressions for the sub-sample of individuals who have heard of cryptocurrencies before. Marginal effects for the three categories of the variable on attitudes to cryptocurrencies are presented in Columns A_1 - A_3 and Columns B_1 - B_3, respectively, along with robust standard errors in brackets. The first model (A_1 - A_3) incorporates two continuous indices capturing the reward perceptions and risk perception of cryptocurrencies among the individuals who have heard of them. The second model (B_1 - B_3) also incorporates two interaction terms between financial literacy and the reward and risk perceptions on cryptocurrencies. The remaining specification is identical to that of Table 3.2.

	Own	***Intend to own***	***Not intend to own***	***Own***	***Intend to own***	***Not intend to own***
	(A_1)	(A_2)	(A_3)	(B_1)	(B_2)	(B_3)
Financial literacy	-0.485***	0.138	0.348*	-0.194	-0.029	0.223
	[0.162]	[0.183]	[0.185]	[0.234]	[0.253]	[0.269]
Reward perception	0.485***	0.616***	-1.101***	0.572***	0.502***	-1.074***
	[0.021]	[0.022]	[0.020]	[0.081]	[0.083]	[0.097]
Fin. Literacy*Reward perception	–	–	–	-0.178	0.235	-0.057
				[0.158]	[0.166]	[0.191]
Risk perception	-0.036*	0.010	0.026	0.085	-0.002	-0.083
	[0.019]	[0.023]	[0.024]	[0.063]	[0.072]	[0.081]
Fin. Literacy*Risk perception	–	–	–	-0.244**	0.027	0.217
				[0.121]	[0.140]	[0.152]
Digital literacy	0.081***	0.066***	-0.148***	0.082***	0.066***	-0.148***
	[0.017]	[0.019]	[0.020]	[0.017]	[0.019]	[0.020]
Inflectional FTR	-0.070**	0.158***	-0.089**	-0.070**	0.158***	-0.089**
	[0.030]	[0.038]	[0.035]	[0.030]	[0.038]	[0.035]
Preference for cash	0.001	-0.006	0.005	0.001	-0.006	0.005
	[0.008]	[0.009]	[0.009]	[0.008]	[0.009]	[0.009]
Male	0.072***	0.019*	-0.091***	0.072***	0.019*	-0.091***
	[0.009]	[0.010]	[0.010]	[0.009]	[0.010]	[0.010]
Log(Household income per capita)	-0.001	0.021	-0.020	-0.001	0.022	-0.022
	[0.025]	[0.029]	[0.030]	[0.025]	[0.029]	[0.030]
Log(Household income per capita)^2	-0.001	-0.007	0.008	-0.001	-0.007	0.008
	[0.007]	[0.008]	[0.008]	[0.007]	[0.008]	[0.008]
Log(Household income per capita)^3	0.001	0.001	-0.001	0.001	0.001	-0.001
	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]
Missing household income p.c.	-0.021	-0.015	0.036	-0.021	-0.016	0.036
	[0.030]	[0.033]	[0.034]	[0.030]	[0.033]	[0.034]
%Fin. literacy effect	*-40.95%*	*5.88%*	*7.21%*	*-18.97%*	*-2.61%*	*4.97%*
#Observations		8,734			8,734	
Log-likelihood		-5,855.7			-5,852.3	
Wald χ^2		2,134.6***			2,133.6***	

The estimates in columns B_1-B_3 produce a negative interaction term between financial literacy and the cryptocurrency risk perception on the probability of owning cryptocurrencies. The effect of the interaction term is large in magnitude and the effect of financial literacy diminishes both in size and significance. Hence, it is confirmed that the negative effect of financial literacy on cryptocurrency ownership is driven by a different perception of risk regarding cryptocurrencies by the more financially literate, compared to less financially literate individuals[40]. All main financial literacy effects on attitudes to cryptocurrencies diminish, both in terms of magnitude and significance, in the specification with the interaction terms between financial literacy, reward and risk.

3.5.3 Validation: Financial-literacy constituents and intertemporal preferences

The inquiry into the mechanics of the relationship between financial literacy and attitudes to cryptocurrencies suggests that the financially literate have an enhanced ability to evaluate the relative risk of owning cryptocurrencies over alternative assets and other types of investment activity. In this section, I conduct two sets of exercises, aiming to validate this conjecture.

In *Table 3.16*, I estimate a multinomial probit regression for the full sample, introducing four new variables which correspond to the four distinct financial-literacy constituent concepts, namely the understanding of financial risk, the score on understanding inflation, the score on understanding simple interest (numeracy), and the score on understanding interest compounding. In this specification, I omit the country fixed effects, to avoid multicollinearity with my four country-level scores. The individual financial-literacy constituent variables are computed as $FL_{constituent}^{individual} = \prod \frac{FL_{constituent}^{country} FL_{gender}^{match} \ FL_{matce}^{matched} FL_{income}^{matched}}{\mathrm{FL}_{\mathrm{country}}^{4}}$, where $FL_{constituent}^{country}$ refers to the country scores in each of the four distinctive financial-literacy concepts in the S&P 2014 Global Financial Literacy Survey and $\mathrm{FL}_{\mathrm{country}}^{4}$ refers to the overall country-level score on financial literacy, raised to the power of four. This exercise creates four individual level variables in the merged dataset, which remove country level differences in overall financial literacy.

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40 The weighted pairwise correlation matrix in the Appendix 1 Table A5 has already indicated a positive correlation between financial literacy and the perception about the risk of cryptocurrencies, and a bigger negative correlation with the perception about the reward from cryptocurrencies. This is also confirmed in the mean differences between the FLH and the FLL groups in the Appendix 1 Table A4.

Table 3.16

The effect of the constituent concepts of financial literacy

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies and robust standard errors are presented in brackets. Instead of a single financial literacy proxy, the specification includes the four financial literacy constituents, i.e. measures that approximate financial knowledge related to financial risk, inflation, interest/numeracy, and compound interest. Except for country dummy variables, which are excluded, the remaining specification is identical to that of Table 3.2, and it also incorporates 15 interaction terms between financial literacy and country.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***
	(1)	(2)	(3)	(4)
Fin. Literacy I: Financial risk	-0.066***	-0.058***	0.042	0.082***
	[0.017]	[0.020]	[0.029]	[0.027]
Fin. Literacy II: Inflation	-0.005	0.021	-0.247***	0.232***
	[0.015]	[0.019]	[0.028]	[0.027]
Fin. Literacy III: Interest/numeracy	0.012	0.074**	0.446***	-0.532***
	[0.025]	[0.031]	[0.043]	[0.041]
Fin. Literacy IV: Compound interest	0.035**	-0.051***	-0.225***	0.241***
	[0.016]	[0.020]	[0.029]	[0.028]
Digital literacy	0.126***	0.142***	-0.078***	-0.190***
	[0.012]	[0.014]	[0.021]	[0.019]
Inflectional FTR	-0.002	0.019**	-0.127***	0.110***
	[0.006]	[0.008]	[0.011]	[0.010]
Preference for cash	0.017***	0.015**	-0.032***	0.001
	[0.005]	[0.006]	[0.009]	[0.008]
Male	0.063***	0.049***	0.090***	-0.202***
	[0.006]	[0.007]	[0.010]	[0.009]
Log(Household income per capita)	0.070***	0.071***	-0.161***	0.021
	[0.012]	[0.014]	[0.019]	[0.018]
Log(Household income per capita)^2	0.001	-0.005	-0.046*	0.051**
	[0.015]	[0.018]	[0.025]	[0.022]
Log(Household income per capita)^3	-0.001	0.004	0.012*	-0.016***
	[0.004]	[0.005]	[0.007]	[0.006]
Missing household income p.c.	0.001	-0.001	-0.001	0.001**
	[0.000]	[0.000]	[0.000]	[0.000]
%Financial risk effect	*-15.88%*	*-9.56%*	*2.23%*	*5.63%*
#Observations	13,267			
Log-likelihood	-14,848.4			
Wald χ^2	2,527.4***			

The estimates in Table 3.16 show that understanding financial risk is negatively associated with cryptocurrency ownership. It is also negatively associated with the intention to own in the future and positively associated with not having heard of cryptocurrencies. Among the basic four financial-literacy components, understanding financial risk is the one variable that exerts a significant negative impact on any favourable attitudes to cryptocurrencies. In contract, understanding interest compounding seems to be positively associated with cryptocurrency ownership. Understanding compounding exerts negative effects on both the positive and the negative inclination towards future ownership. Overall, the results of this exercise are in accordance with the interpretation that understanding financial risk, i.e. a key financial literacy skill, is negatively related to cryptocurrency ownership and the inclination in favour of future ownership. Finally, there is a negative effect from understanding inflation and a positive effect from understanding interest rates on not intending to own cryptocurrencies in the future.

In *Table 3.17*, I conduct one final exercise aiming to test the validity of my proposed moderator in a broader context using the OECD survey data on 3 Asian countries. If the financially literate are negatively disposed towards cryptocurrencies due to being in a better position to evaluate the financial risk entailed in their ownership compared to other investment alternatives, does this mean that the more financially-literate present-biased individuals will be in a better position to avoid any innate inclination towards high-risk investment, such as that in cryptocurrencies? To evaluate this question, I use a risk preference proxy enabled by the present orientation variable[41] and present multinomial probit estimates, in which I introduce an interaction term between financial literacy and the present orientation bias variable. The results of Table 3.17 show that the risk preference exerts a large positive impact on cryptocurrency ownership. The interaction term between financial literacy and present bias show no impact on the probability of owning cryptocurrencies or on other behaviour. Evidently, greater financial literacy skills among individuals who may be more prone to risky behaviour due to present bias might help prevent some of the innate urges to rush into riskier investment decisions.

[41] The OECD survey formulates the question with the choice of answer options the following: "To what extent do the following statements describe you?": "I tend to live for today and let tomorrow take care of itself". With answer options of three: "Describes me very well", "Describes me somewhat" or "Does not describe very well".

Table 3.17

The effect of interaction terms between financial literacy and present orientation

This table reports selected estimates from the OECD Consumer Insights Survey on Cryptoassets (2019) of the determinants of attitudes to cryptocurrencies from a multinomial probit regression. Marginal effects for the for categories of the variable on attitudes to cryptocurrencies (Currently owning; Previously owning; Never held; and, Never heard of) are presented, along with robust standard errors in brackets. The specification includes control variables for labour market status (8 dummies) and a constant term.

	Currently hold **[1]**	Previously held **[2]**	Never held **[3]**	Never heard of **[4]**
Financial literacy	-0.188**	0.059	0.320***	-0.143***
	[0.074]	[0.087]	[0.076]	[0.028]
Financial literacy*Present orientation	0.014	-0.008	0.001	-0.001
	[0.018]	[0.016]	[0.015]	[0.006]
Present orientation	0.025	0.03	-0.046	0.005
	[0.033]	[0.030]	[0.029]	[0.011]
Technological literacy	0.038*	-0.02	-0.028	0.001
	[0.020]	[0.024]	[0.022]	[0.007]
Risk preference	0.117***	0.025**	-0.046***	-0.023***
	[0.012]	[0.011]	[0.012]	[0.005]
Male	0.012	0.024*	-0.01	-0.009
	[0.016]	[0.014]	[0.015]	[0.006]
Age: 18-25	0.198***	0.034	-0.059	-0.035*
	[0.054]	[0.047]	[0.049]	[0.021]
Age: 26-35	0.210***	0.066	-0.095**	-0.039**
	[0.049]	[0.042]	[0.046]	[0.020]
Age: 36-45	0.160***	0.019	-0.037	-0.032*
	[0.048]	[0.040]	[0.043]	[0.019]
Age: 46-55	0.163***	-0.022	-0.028	-0.025
	[0.046]	[0.039]	[0.041]	[0.019]
Age: 56-65	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Occupation: Self-Employed	0.044	0.016	-0.057	0.007
	[0.048]	[0.042]	[0.041]	[0.017]
Full-time employee	0.079*	0.061	-0.080**	-0.011
	[0.044]	[0.038]	[0.037]	[0.015]
Part-time employee	0.075	0.036	-0.043	-0.014
	[0.052]	[0.046]	[0.046]	[0.018]
Student	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Unemployed	0.031	0.055	-0.057	-0.005
	[0.055]	[0.045]	[0.045]	[0.018]
Inactive	0.068	-0.089	0.022	0.006
	[0.092]	[0.087]	[0.077]	[0.029]
Retired	0.017	-0.082	-0.008	0.028
	[0.089]	[0.074]	[0.072]	[0.031]
Homemaker	0.041	0.006	-0.059	0.012
	[0.062]	[0.053]	[0.052]	[0.021]

Pre-sixteen	-0.117*	-0.105*	0.106*	0.019
	[0.066]	[0.056]	[0.064]	[0.021]
Education: No qualifications	{Ref.}	{Ref.}	{Ref.}	{Ref.}
A-levels, GNVQ or college	-0.113	-0.180***	0.187**	0.009
	[0.071]	[0.062]	[0.073]	[0.023]
University (Bachelor)	-0.033	-0.088	0.12	-0.03
	[0.071]	[0.066]	[0.075]	[0.023]
Higher university degree	-0.008	-0.097	0.142**	-0.036
	[0.069]	[0.062]	[0.072]	[0.023]
House owner	0.140***	0.086***	-0.076***	-0.047***
	[0.017]	[0.017]	[0.017]	[0.007]
Log(Household income-PPP)	-0.205***	-0.078	-0.009	0.104***
	[0.065]	[0.059]	[0.061]	[0.024]
Log(Household income-PPP)^2	0.054***	0.021	-0.002	-0.027***
	[0.016]	[0.015]	[0.015]	[0.006]
Log(Household income-PPP)^3	-0.003***	-0.001	0.001	0.001***
	[0.001]	[0.001]	[0.001]	[0.000]
Philippines	0.186***	0.070***	-0.081***	-0.046***
	[0.024]	[0.021]	[0.024]	[0.009]
Vietnam	0.046**	0.054***	-0.066***	-0.001
	[0.021]	[0.020]	[0.023]	[0.009]
% Fin. literacy effect	*-27.6%*	*9.7%*	*47.6%*	*-75.6%*
Predicted probability	*0.4068*	*0.2111*	*0.4562*	*0.1344*
No. of Observations	*3,428*	*3,428*	*3,428*	*3,428*

3.6. Concluding remarks

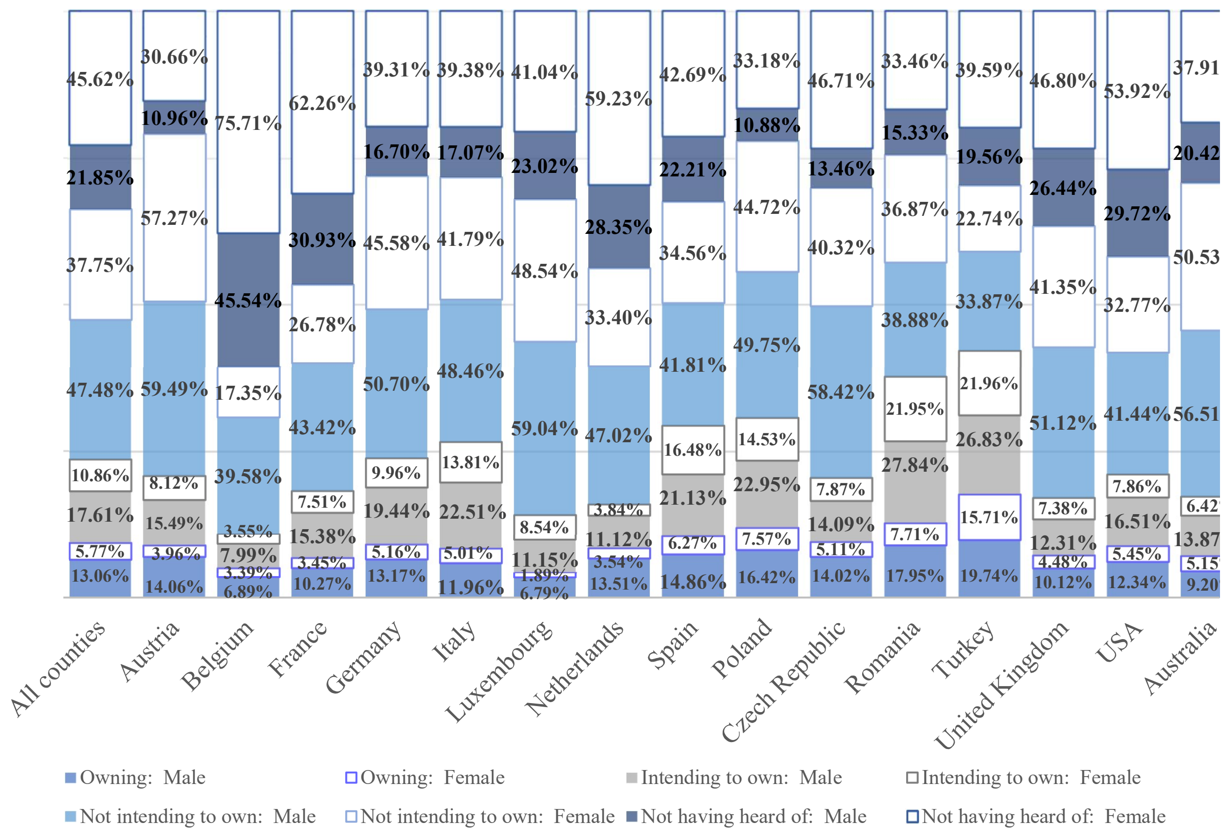
This study examines the significant role of financial literacy in the formation of attitudes to cryptocurrency ownership globally. I show that financial literacy exerts a statitically significant negative impact on the probability of owning cryptocurrency. Financially literate individuals are also more likely to have no intention of owning cryptocurrencies in the future. Overall, they are more likely to have heard about cryptocurrencies and be aware of them. my analysis also shows that the size of these effects is economically important and robust in different specifications, when using different financial literacy definitions, and when including a rich set of control variables. I also show my results are robust when using a sample selection model, with awareness about cryptocurrencies at the first stage. They are robust to an IV model, for endogeneity due to measurement error or omitted variable, which may confound the estimates of financial literacy. Moreover, I document the external validity of my financial literacy proxy and the robustness of my findings when using a separate sample of retail investors from 3 Asian countries.

Examining the moderators of the established relationships, I find that the effect of financial literacy remains unaltered in models with interaction terms between financial literacy and digital literacy, preference for cash/informality, age, and financial advice, *inter alia*. The one moderator that explains the relationship between financial literacy and attitudes to cryptocurrencies is perception of the risk that cryptocurrencies entail, in comparison to alternative assets. In models with interaction terms between financial literacy and risk perception, significant interaction effects are found, and the effect of the financial literacy variable diminishes in size and significance. This conjecture is confirmed by the greater negative impact of the financial-risk constituent of the financial literacy measure on ownership and on the intention to own cryptocurrencies in the future. It is also confirmed by a large negative effect on ownership by the interaction term between financial literacy and intertemporal preferences towards a present bias, as approximated by the inflectional FTR of the individual's language. I interpret my results as indicative that greater financial literacy skills among individuals whose linguistic background is associated with present-biased beliefs might mitigate some of the temptation to engage in high-risk investment decisions.

The importance of financial literacy in modern economies cannot be overemphasized. Financial literacy has a clear public good element to it, as it has been conceptually linked to macroeconomic financial stability. Lusardi et al. (2017) assess that differences in financial knowledge formed early in life can explain some 35-40% of retirement wealth inequality in the United States. I find my findings are complementary to this recent insight, by suggesting that financial literacy is negatively associated with investment decisions towards highly volatile assets such as cryptocurrencies. More recently, Foley et al. (2019) present evidence suggesting that some 46% of bitcoin transactions are related to illegal activity, and some USD10 billion in assets are managed by dedicated 'cryptofunds' (Rooney and Levy, 2018). Such activity is less likely to be captured in surveys. my survey inquiry comes is a timely complement to that recent evidence. It is conducive to shedding light on the demand side of cryptocurrencies and suggests that apart from illegal and exclusive activity, a large part of the cryptocurrency market comprises of unsophisticated investors with lower financial literacy skills. These investors are likely to overestimate the reward prospects in cryptocurrencies and underestimate the risk involved in such investments. For any new financial instrument or alternative asset to become established, less volatile and less likely to be subject to manipulation, the market needs to be dominated by sophisticated investors and formal/legitimate uses. my findings and the recent evidence regarding the uses of bitcoin suggest that the current state of the market for cryptocurrencies is far from that. Hence, it is entirely appropriate that policy makers in central banks and other regulatory bodies should be concerned. Efforts are needed to increase the public understanding of the supply side and enable an inquiry into the motivations and incentives of market participants in the demand side of cryptocurrencies. This will increase awareness and transparency, and might ultimately make this market less volatile, more predictable and less subject to any manipulation.

I contribute to the financial economics literature by presenting novel evidence suggesting that the financially literate are less likely to invest in the cryptocurrency market, due to a more informed perception regarding the risks involved compared to alternative assets. With most economic models relying on the premise of rational agents, any cognitive skills that are likely to induce such behaviour, such as financial literacy in my setting, are likely to be conducive to the validity and predictive power of these economic models. Such models and predictions are essential for the highly volatile and largely unpredictable cryptocurrency market. I contribute to the literature on financial education and education economics. my findings may potentially be considered when designing financial education related to FinTech and investor participation, by including elements on digital finance with the objective of providing a broader view on the subject. They are also relevant to regulators and supervisors with responsibility for financial consumer protection and market stability.

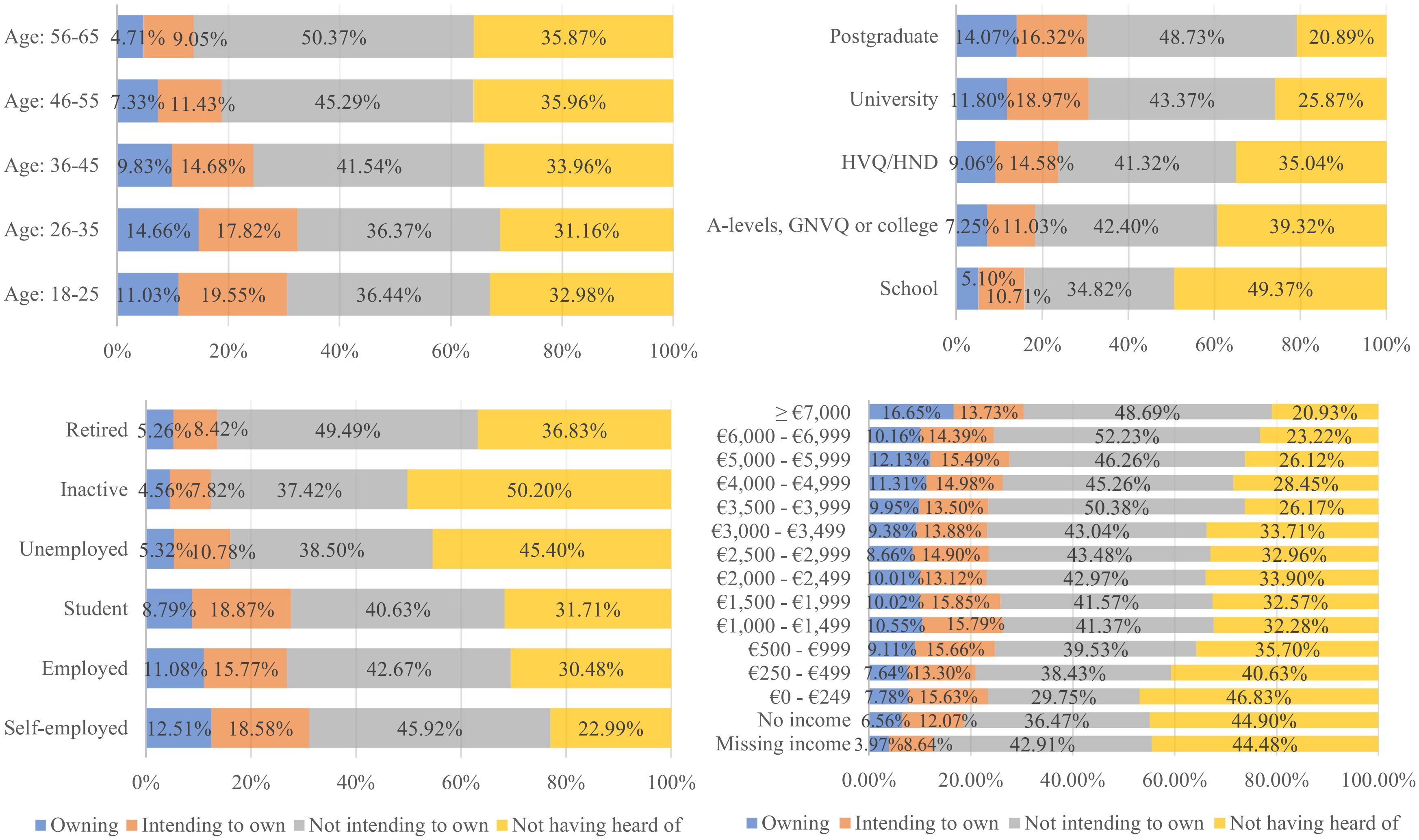
Appendices 1



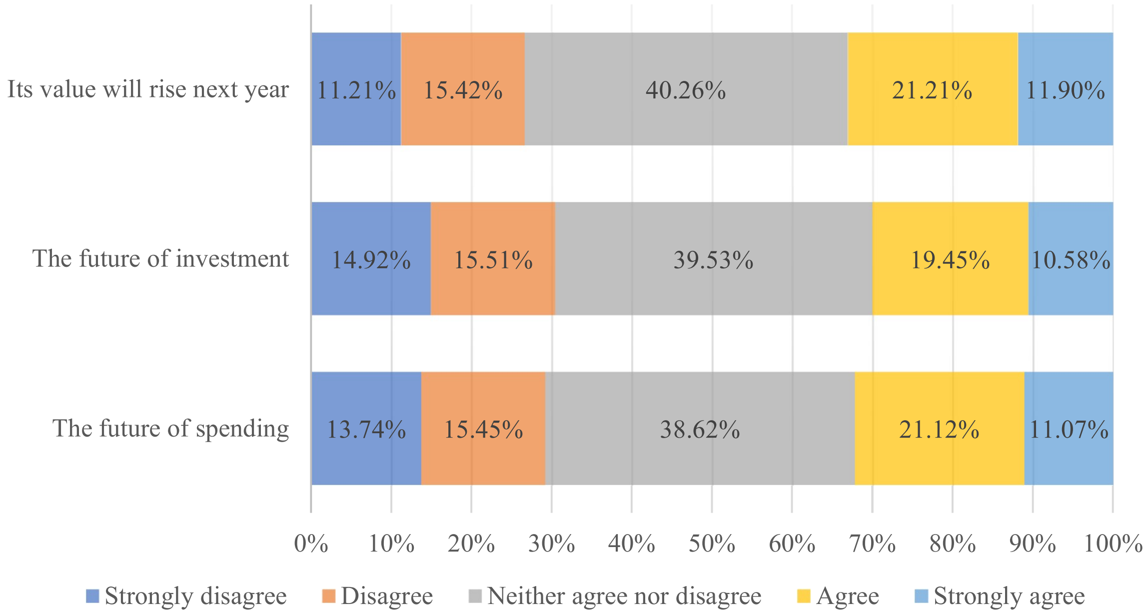
Appendix 1 Chapter 3 Figure A1

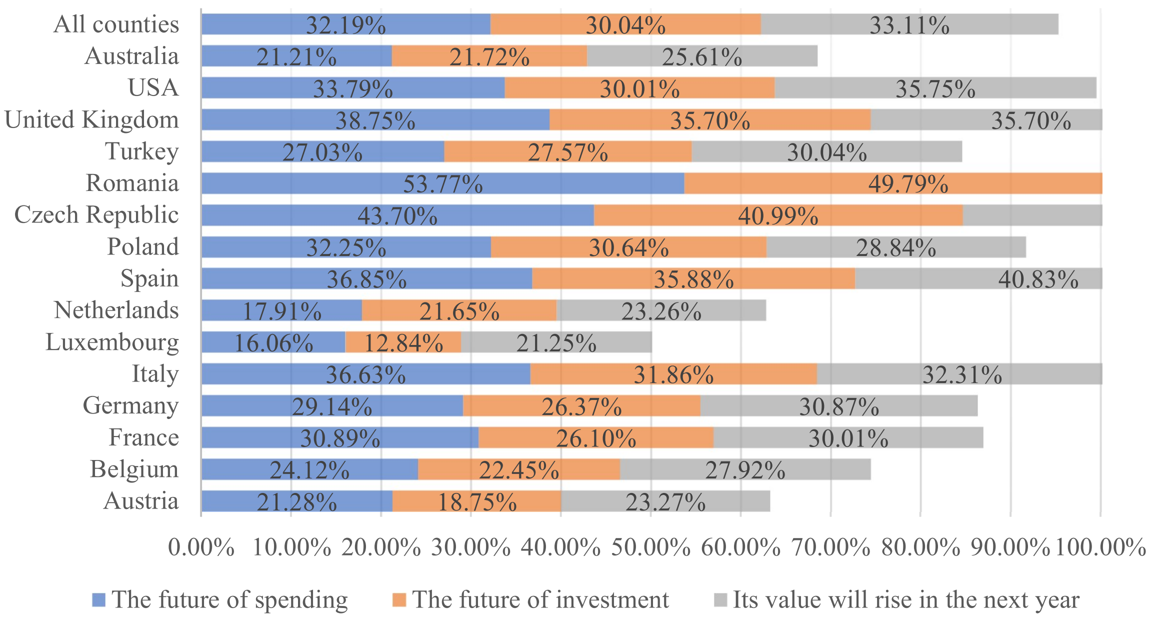
Attitudes to cryptocurrencies and gender (ING International Survey on Mobile Banking, 2018)

This figure presents the demographic composition of attitudes to cryptocurrencies by gender. Each bar of the figure presents the weighted frequencies of the four categories for each gender, for instance, (i) owning cryptocurrency; (ii) not owning but intending to own; (iii) not owning and not intending to own, and (iv) not having heard of cryptocurrencies before. The first bar shows the frequencies for the sample overall, by gender, and then, the remaining bars present the frequencies by gender for each of the countries in my sample. Females are presented in white boxes in each bar.



Appendix1 Chapter 3 Figure A2
Attitudes to cryptocurrencies by demographic group (ING International Survey on Mobile Banking 2018). This figure presents the demographic composition of attitudes to cryptocurrencies by age group, education category, labor market status, and income bracket. All figures are weighted.

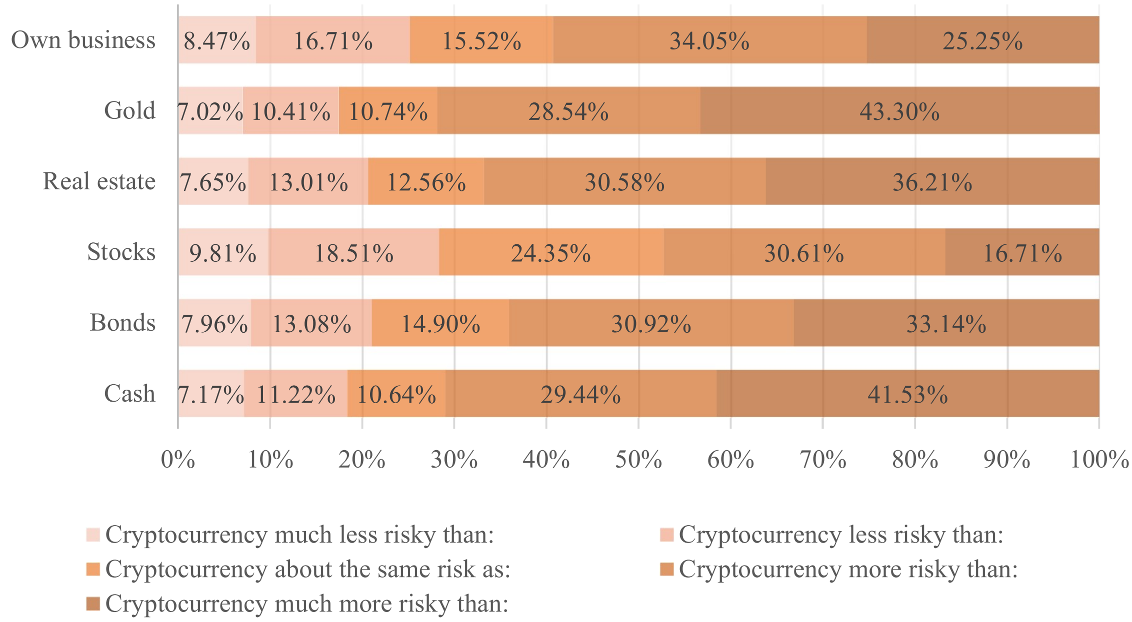


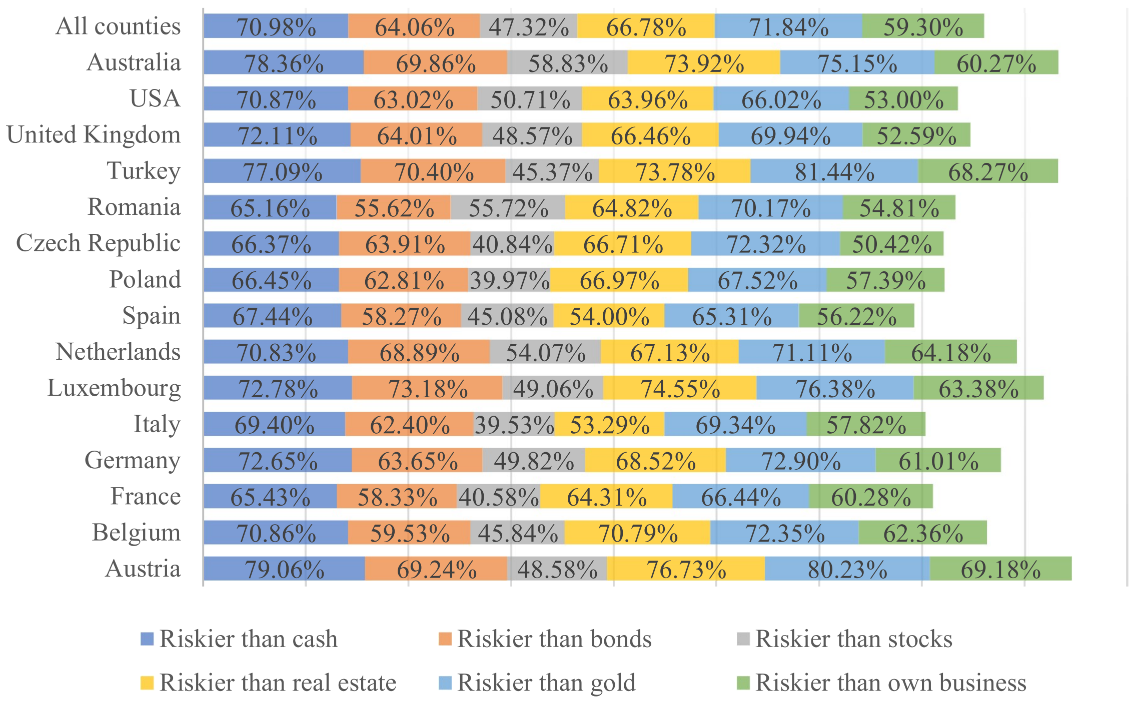


Appendix1 Chapter 3 Figure A3

Reward perceptions of cryptocurrencies

This figure presents the response frequencies in each of the 3 cryptocurrency reward perception questions. The top figure presents the percentages of individuals who strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree with each of the three statements regarding the prospects of cryptocurrencies, such as bitcoin. The bottom picture presents the fraction of individuals who agree or strongly agree with each of the three statements in the overall sample, and then for each country in the sample. All figures are weighted.





Appendix 1 Chapter 3 Figure A4

Risk perceptions of cryptocurrencies

This figure presents the response frequencies in each of the 6 cryptocurrency risk perception questions. The top figure presents the percentages of individuals who find that cryptocurrency entails much lower risk, lower risk, about the same risk, higher risk, and much higher risk than each of the 6 alternatives, for instance, cash, bonds, stocks, gold, real estate/property funds, investment in own business. The bottom picture presents the fraction of individuals who find that holding cryptocurrency entails higher risk or much higher risk, compared to holding each of the 6 alternatives in the overall sample, and then for each country in the sample. All figures are weighted.

Appendix 1 Chapter 3 Table A1

Risk and return characteristics of bitcoin and other instruments

This table presents calculations of the standard investment risk and return characteristics of bitcoin, and other financial instruments, namely cash, bonds, equities, gold, and real estate. The left panel entails calculations for the 3-year period between 1.1.2016 - 1.1.2019, and the right panel presents calculations for the 1-year period between 1.1.2018 – 1.1.2019. Columns 1 and 5 present the annualized return and Columns 2 and 6 present the standard deviation. Columns 3 and 7 present the Sharpe ratio. Columns 4 and 8 present the Sortino ratio. The analysis employs 0.5% as the risk-free rate ($\bar{R}$) for the calculation of the Sharpe and Sortino ratios. The Sharpe ratio is calculated as the excess reward of each asset (*j*) over the risk-free rate divided by the standard deviation, i.e. $Sharpe_j = \frac{R_j - \bar{R}}{SD_j}$. The Sortino ratios is calculated as the excess reward over the risk-free rate divided by the standard deviation of the downside, i.e. $Sortino_j = \frac{R_j - \bar{R}}{SD_j^D}$.The data stems from Thomson Reuters and Bloomberg. The US T-Bill is used as a cash proxy. The Bloomberg Barclays GDP Core Developed Govt AA- or Above TR Hedged USD are used to display sovereign bonds. The SP GLOBAL 1200 total return index is used for equities. The Gold Bullion LBM USD/t, US T-Bill for gold; The MSCI ACWI REAL ESTATE USD price index is used for real estate. Bitcoin's daily price is from Coindesk.

	3-year period (2016-2019)				1-year period (2018)			
	Return % (ann.)	SD % (ann.)	Sharpe	Sortino	Return % (ann.)	SD % (ann.)	Sharpe	Sortino
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bitcoin	70.76	73.35	0.72	1.40	-73.42	79.63	-1.02	-2.08
Cash	1.39	0.05	-	-	2.06	0.02	-	-
Bonds	3.42	3.39	0.59	0.87	2.04	2.77	-0.03	-0.02
Equities	9.01	10.89	0.67	0.95	-10.47	12.91	-1.01	-1.28
Gold	8.96	11.99	0.59	0.94	-1.56	9.83	-0.41	-0.52
Real Estate	5.02	10.24	0.31	0.48	-10.40	10.67	-1.19	-1.51

Appendix 1 Chapter 3 Table A2

Summary statistics – OECD Consumer Insights Survey on Cryptoassets (2019)

This table reports averages for all individuals in the OECD 2019 Consumer Insights Survey on Cryptoassets (Column 1) in three countries, namely Malaysia, Philippines, and Vietnam. It reports averages for individuals currently owning cryptocurrency (Column 2), for individuals previously owning cryptocurrency (Column 3), for those who never held any cryptocurrency (Column 4), and for individuals who have not heard of cryptocurrencies before (Column 5). Column 6 reports mean differences and asterisks for the levels of significance from t-tests between individuals currently owning and those who never held any cryptocurrencies before. The asterisks denote the following levels of significance: *** p<0.01, ** p<0.05, * p<0.1. The financial literacy variable is calculated as the number of correct response in the following two questions: "*An investment with a high return is likely to be high risk*", and "*High inflation means that the cost of living is increasing rapidly*". The response categories involved "True", "False", and "I don't know".

	(1)	(2)	(3)	(4)	(5)	(6)	
	All	**Currently hold**	**Previously held**	**Never held**	**Never heard of**	**Difference (2)-(4)**	**[Sig.]**
	[3,428]	*[1,261]*	*[500]*	*[1,066]*	*[601]*		
Panel A: Sample composition							
All countries	–	36.8%	14.6%	31.1%	17.5%	–	
Malaysia *[1,138]*	–	30.1%	13.9%	41.9%	14.1%	–	
Philippines *[1,144]*	–	39.2%	12.8%	25.4%	22.6%	–	
Vietnam *[1,146]*	–	41.0%	17.1%	26.0%	15.9%	–	
Panel B: Individual characteristics and mean differences							
Financial literacy	1.624	1.697	1.644	1.675	1.361	0.053	
Digital literacy	2.602	2.679	2.580	2.567	2.521	0.099	***
Risk tolerance	2.164	2.388	2.140	1.956	2.083	0.248	***
Present orientation	1.983	2.108	1.960	1.765	2.128	0.148	***
Male	49.8%	50.8%	52.2%	49.1%	46.9%	-0.015	
Age	36.07	36.29	36.16	37.72	32.63	0.134	***
Household income-PPP	4,318.0	5,198.1	4,402.1	3,966.8	2,606.3	796.0	***
Home owner	58.2%	74.7%	65.0%	50.4%	32.0%	0.097	***
Occupation: Self-Employed	12.4%	10.7%	11.0%	13.8%	14.6%	-0.003	**
–"–: Full-time employee	63.9%	75.9%	71.6%	58.2%	42.8%	0.043	***
–"–: Part-time employee	5.8%	5.4%	5.2%	6.0%	7.0%	0.002	
–"–: Unemployed	5.5%	2.2%	3.4%	7.3%	11.0%	-0.012	***
–"–: Inactive	5.5%	2.6%	4.8%	5.8%	11.8%	-0.022	***
–"–: Retired	1.4%	0.6%	0.4%	1.5%	3.7%	0.002	**
–"–: Homemaker	1.8%	0.5%	1.0%	3.6%	1.8%	-0.005	***
–"–: Student	3.6%	2.1%	2.6%	3.9%	7.3%	-0.005	**
Education: No qualifications	2.0%	1.2%	2.0%	0.8%	5.7%	-0.008	
–"–: Pre-sixteen	19.0%	10.2%	17.4%	18.5%	39.8%	-0.073	***
–"–: A-levels, GNVQ or college	9.4%	5.0%	5.6%	13.5%	14.6%	-0.006	***
–"–: University (Bachelor)	57.9%	66.4%	64.6%	58.3%	33.9%	0.018	***
–"–: Higher university degree	11.7%	17.3%	10.4%	8.9%	6.0%	0.069	***
Malaysia [1,138 obs.]	33.2%	27.2%	31.6%	44.8%	26.6%	-0.044	***
Philippines [1,144 obs.]	33.4%	35.5%	29.2%	27.3%	43.1%	0.063	***
Vietnam [1,146 obs.]	33.4%	37.3%	39.2%	28.0%	30.3%	-0.019	***

Appendix 1 Chapter 3 Table A3

Country-level financial literacy scores

This table reports the representative country-level scores in financial literacy, its 4 constituent concepts, and the figures by gender, age group and income group for the selected sample of 18 countries from the S&P 2014 Global Financial Literacy Survey. The figures are publicly available at: https://www.cssf.lu/fileadmin/files/Protection_consommateurs/Education_financiere/SP_Ratings_Global_FinLit-Summary_Statistics_as_of_12152015.xls

	Country		Constituent concepts			Gender			Age group		Income group	
Country	score	Financial risk	Inflation	Interest/ numeracy	Compound interest	Males	Females	15-34	35-54	>55	Top 60%	Bottom 40%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
United States	57%	69%	63%	52%	61%	62%	52%	57%	65%	57%	64%	47%
Australia	64%	69%	63%	61%	68%	72%	56%	64%	67%	72%	73%	50%
Austria	53%	59%	64%	61%	52%	55%	51%	56%	54%	54%	59%	44%
Belgium	55%	65%	62%	58%	53%	59%	52%	63%	58%	56%	59%	50%
France	52%	50%	67%	60%	54%	56%	48%	46%	58%	53%	55%	47%
Germany	66%	74%	62%	66%	64%	72%	60%	72%	82%	61%	73%	55%
Italy	37%	40%	55%	55%	38%	45%	30%	47%	39%	35%	44%	27%
Luxembourg	53%	53%	67%	57%	51%	61%	46%	58%	49%	57%	56%	50%
Netherlands	66%	73%	67%	59%	69%	75%	58%	71%	71%	68%	71%	60%
Spain	49%	56%	65%	59%	43%	50%	48%	47%	51%	56%	54%	43%
United Kingdom	67%	69%	66%	71%	68%	66%	68%	67%	71%	68%	70%	63%
Czech Republic	58%	56%	64%	71%	54%	65%	53%	59%	60%	61%	61%	55%
Poland	42%	39%	63%	60%	45%	49%	36%	50%	44%	39%	44%	40%
Romania	22%	22%	49%	37%	25%	22%	22%	30%	23%	19%	25%	17%
Turkey	24%	23%	47%	49%	45%	28%	19%	28%	23%	16%	26%	20%
Malaysia	36%	49%	42%	39%	56%	38%	33%	42%	27%	36%	39%	33%
Philippines	25%	26%	53%	42%	43%	24%	26%	26%	23%	22%	33%	23%
Vietnam	24%	25%	55%	31%	46%	28%	21%	30%	17%	33%	22%	13%

Appendix 1 Chapter 3 Table A4

Weighted summary statistics by financial literacy group

This table reports weighted averages for all individuals (Column 1). It reports weighted averages for individuals in the high financial literacy group in Column 2 (FLH), and for individuals in the low financial literacy group in Column 3 (FLL). I employ a binary 'High financial literacy' indicator, which stems from the computation of percentiles of financial literacy for each country separately. Individuals are considered to be of 'high financial literacy' (FLH) if the percentile of their financial-literacy score within their country is greater than 50. If it is lower than or equal to fifty within country, they are considered to be of 'low financial literacy' (FLL). Column 4 reports mean differences and asterisks for the levels of significance from weighted t-tests between individuals in the high and the low financial literacy group. The asterisks denote the following levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

	All	FLH	FLL	Difference	[Sig]
	(1)	(2)	(3)	(4)	
Financial literacy	0.514	0.539	0.493	0.046	***
Digital literacy	0.478	0.505	0.456	0.049	***
Inflectional FTR	0.334	0.326	0.340	-0.014	
Preference for cash	0.835	0.824	0.845	-0.021	***
Household income per capita	1,078.3	1,355.2	851.9	503.3	***
Missing income	10.6%	11.0%	10.2%	0.008	
Male	48.6%	78.2%	24.1%	0.541	***
Age	42.0471	40.9386	42.9616	-2.023	***
Young (<45)	54.5%	58.6%	51.2%	0.074	***
Married	49.7%	50.2%	49.2%	0.010	
Single	22.9%	25.2%	21.1%	0.042	***
In a relationship	17.5%	17.7%	17.3%	0.004	
Widowed/Divorced/Separated	9.9%	6.9%	12.4%	-0.055	***
Household size	2.6978	2.6155	2.7656	-0.150	***
Pre-sixteen education	11.2%	9.1%	12.9%	-0.039	***
A-levels, GNVQ or college	34.7%	32.2%	36.8%	-0.046	***
Higher vocational education or HND	17.8%	16.7%	18.6%	-0.019	***
University (Bachelors)	22.2%	24.6%	20.2%	0.044	***
Higher university degree	14.2%	17.5%	11.5%	0.060	***
Occupation: Self-Employed	6.4%	7.1%	5.8%	0.013	***
–"– Full-time employee	48.0%	61.3%	37.0%	0.243	***
–"– Part-time employee	12.0%	8.2%	15.2%	-0.070	***
–"– Student	7.1%	7.1%	7.1%	0.000	
–"– Unemployed	6.4%	3.5%	8.8%	-0.053	***
–"– Inactive	9.6%	4.5%	13.7%	-0.092	***
–"– Retired	10.5%	8.3%	12.4%	-0.041	***
Fin. advice: An independent financial advisor or bank advisor	19.8%	19.4%	20.2%	-0.008	
–"– My friends/family	8.1%	8.2%	8.1%	0.001	
–"– The internet and specialist websites	27.8%	30.6%	24.7%	0.059	***
–"– An online computer program or algorithm for tailored advice	6.7%	7.0%	6.4%	0.006	
–"– No financial advice	37.6%	34.8%	40.6%	-0.058	***
Reward perception	0.602	0.597	0.607	-0.011	**
Risk perception	0.732	0.745	0.719	0.026	***
Digital currencies – e.g. bitcoin – are the future of spending online	3.003	2.982	3.025	-0.043	*
- " - investment as storage of value	2.953	2.917	2.991	-0.074	***
I think the value of digital currencies – e.g. bitcoin – will increase in the next 12 months	3.072	3.050	3.095	-0.046	*
Cryptocurrency riskier than cash	3.870	3.915	3.820	0.095	***
- " - bonds	3.682	3.770	3.588	0.182	***
- " - stocks	3.259	3.328	3.185	0.143	***
- " - real estate/funds	3.747	3.813	3.676	0.137	***
- " - gold	3.907	3.957	3.853	0.105	***
- " - investing in own business	3.509	3.571	3.442	0.130	***
Lack of awareness regarding online payment providers	0.282	0.255	0.304	-0.049	***
Mobile banking usage for efficient personal financial management	37.1%	40.2%	34.4%	0.058	***

Appendix 1 Chapter 3 Table A5

Weighted pairwise correlation matrix

This table reports the weighted pairwise correlation matrix for all individuals in the ING 2018 International Survey on Mobile Banking. The asterisk denotes the following level of significance: * p<0.05. The financial literacy variable is calculated as the individual average of the country financial literacy scores by gender, age group (15-34, 35-54, >55) and income (top 60%, bottom 40%) from the S&P 2014 Global Financial Literacy Survey.

	(1) Owning crypto	(2) Intending to own	(3) Financial literacy	(4) Male	(6) Age	(7) University	(8) Household income	(9) Inflectional FTR	(10) Digital literacy	(11) Preference for cash	(12) Risk perception	(13) Reward perception	(14) Future of spending online	(15) –” – investment/stor. valu	(16) Value ↑in 12 months	(17) Bitcoin riskier than cash	(18) –” – bonds	(19) –” – equities	(20) –” – real estate	(21) –” – gold	(22) –” – own firm
(1) Owning crypto	1.00																				
(2) Intending to own	-0.13*	1.00																			
(3) Financial literacy	-0.06*	-0.12*	1.00																		
(4) Male	0.07*	0.06*	0.15*	1.00																	
(6) Age	0.12*	0.09*	0.11*	0.53*	1.00																
(7) University	-0.10*	-0.11*	0.05*	-0.07*	-0.04*	1.00															
(8) Household income	0.04*	0.07*	-0.22*	0.05*	0.00	-0.05*	1.00														
(9) Inflectional FTR	0.00	-0.04*	0.38*	0.23*	0.08*	0.16*	0.00	1.00													
(10) Digital literacy	0.01	0.06*	-0.41*	-0.01	0.00	-0.01	0.16*	0.02	1.00												
(11) Preference for cash	0.14*	0.12*	-0.02	0.11*	0.09*	-0.12*	0.10*	0.07*	0.01	1.00											
(12) Risk perception	0.03*	0.05*	-0.22*	-0.02	0.02*	-0.06*	0.00	-0.18*	-0.02*	-0.01	1.00										
(13) Reward perception	-0.15*	-0.12*	0.03*	0.06*	0.04*	0.17*	0.03*	0.09*	-0.03*	-0.05*	-0.06*	1.00									
(14) Future of spending online	0.35*	0.35*	-0.20*	-0.02	-0.02*	-0.22*	0.05*	-0.16*	0.09*	0.14*	0.11*	-0.36*	1.00								
(15) –”– investment/stor. value	0.32*	0.33*	-0.20*	-0.01	-0.01	-0.20*	0.05*	-0.16*	0.09*	0.14*	0.11*	-0.33*	0.92*	1.00							
(16) Value ↑in 12 months	0.32*	0.33*	-0.18*	-0.03*	-0.03*	-0.22*	0.04*	-0.16*	0.08*	0.14*	0.10*	-0.35*	0.92*	0.81*	1.00						
(17) Bitcoin riskier than cash	0.31*	0.28*	-0.16*	-0.02	-0.02	-0.17*	0.05*	-0.10*	0.09*	0.11*	0.09*	-0.30*	0.87*	0.68*	0.70*	1.00					
(18) –”– bonds	-0.11*	-0.09*	0.03*	0.03*	0.01	0.09*	0.01	0.06*	-0.01	-0.05*	-0.02	0.77*	-0.27*	-0.25*	-0.27*	-0.22*	1.00				
(19) –”– equities	-0.12*	-0.09*	0.05*	0.07*	0.06*	0.16*	0.03*	0.07*	-0.02*	-0.03*	-0.07*	0.80*	-0.29*	-0.26*	-0.28*	-0.25*	0.54*	1.00			
(20) –”– real estate	-0.11*	-0.13*	0.04*	0.05*	0.03*	0.13*	0.01	0.08*	-0.07*	-0.02	-0.05*	0.71*	-0.31*	-0.28*	-0.29*	-0.26*	0.42*	0.50*	1.00		
(21) –”– gold	-0.11*	-0.08*	0.03*	0.05*	0.03*	0.13*	0.03*	0.06*	-0.07*	-0.04*	-0.06*	0.81*	-0.28*	-0.26*	-0.27*	-0.23*	0.55*	0.59*	0.50*	1.00	
(22) –”– own firm	-0.11*	-0.06*	-0.01	0.04*	0.02	0.13*	0.02	0.05*	0.00	-0.05*	-0.03*	0.79*	-0.26*	-0.23*	-0.25*	-0.22*	0.59*	0.58*	0.43*	0.61*	1.00

Appendix 1 Chapter 3 Table A6

The interaction between financial literacy, years of education and income

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression. Marginal effects for the four categories of the variable on attitudes to cryptocurrencies and robust standard errors are presented in brackets. The remaining specification is identical to that of Table 2, with the exception of the 3rd order polynomial in household income and the replacement of the 5 education categories with a continuous variable capturing years of education. The continuous years of education variable is computed as follows: Individuals with 'Pre-sixteen education' get assigned with 9 years of education. Individuals with 'A-levels, GNVQ or college' get assigned with 12 years of education. Respondents with 'Higher vocational education or HND' get assigned with 14 years. Then, respondents with 'University (Bachelor)' get assigned with 16 years, and individuals with 'Higher university degree' get assigned with 19 years. Finally, the specification also incorporates a triple interaction term between financial literacy, years of education, and the logarithm of monthly PPP-divided household income per capita.

	Own	***Intend to own***	***Not intend to own***	***Not having heard of***
	(A_1)	(A_2)	(A_3)	(A_4)
Financial literacy	-0.245**	0.044	0.915***	-0.715***
	[0.112]	[0.129]	[0.180]	[0.165]
Years of Education	0.007***	0.003	0.017***	-0.027***
	[0.002]	[0.002]	[0.003]	[0.002]
Log(Household income per capita)	0.011***	0.005	0.008	-0.023***
	[0.003]	[0.004]	[0.005]	[0.005]
Fin. literacy*Years of education*Log(Household income p.c.)	-0.001	0.001	-0.001	0.001**
	[0.000]	[0.000]	[0.001]	[0.001]
Digital literacy	0.120***	0.133***	-0.074***	-0.180***
	[0.012]	[0.014]	[0.021]	[0.019]
Inflectional FTR	-0.008	0.131***	-0.042	-0.081***
	[0.019]	[0.025]	[0.028]	[0.024]
Preference for cash	0.012**	0.001	-0.044***	0.031***
	[0.006]	[0.006]	[0.009]	[0.009]
Male	0.068***	0.051***	0.069***	-0.188***
	[0.006]	[0.007]	[0.010]	[0.009]
%Fin. literacy effect	*-34.39%*	*-0.94%*	*30.97%*	*-27.72%*
#Observations	13,267			
Log-likelihood	-14,591.7			
Wald χ^2	2,915.0***			

Appendix 1 Chapter 3 Appendix Table A7

The effect of interaction terms between financial literacy and risk preferences

This table reports selected estimates of the determinants of attitudes to cryptocurrencies from a weighted multinomial probit regression. The asterisks denote the following levels of significance: *** p<0.01, ** p<0.05, * p<0.1.

	Currently hold	**Previously held**	**Never held**	**Never heard of**
	[1]	**[2]**	**[3]**	**[4]**
Financial literacy	-0.191**	0.021	0.331***	-0.131***
	[0.076]	[0.087]	[0.076]	[0.029]
Risk preference	0.096***	0.003	-0.032	-0.013
	[0.033]	[0.029]	[0.028]	[0.011]
Financial literacy*Risk preference	0.012	0.014	-0.008	-0.006
	[0.019]	[0.017]	[0.016]	[0.007]
Technological literacy	0.039**	-0.02	-0.027	-0.001
	[0.020]	[0.024]	[0.022]	[0.007]
Present-biased	0.049***	0.017	-0.045***	0.004
	[0.012]	[0.012]	[0.014]	[0.005]
Male	0.011	0.023	-0.01	-0.009
	[0.016]	[0.014]	[0.015]	[0.006]
Age: 18-25	0.196***	0.035	-0.059	-0.035*
	[0.054]	[0.047]	[0.049]	[0.021]
Age: 26-35	0.209***	0.067	-0.095**	-0.039**
	[0.049]	[0.042]	[0.046]	[0.020]
Age: 36-45	0.159***	0.02	-0.038	-0.033*
	[0.048]	[0.040]	[0.043]	[0.019]
Age: 46-55	0.162***	-0.022	-0.027	-0.026
	[0.046]	[0.039]	[0.041]	[0.019]
Age: 56-65	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Occupation: Self-Employed	0.042	0.015	-0.056	0.007
	[0.048]	[0.041]	[0.041]	[0.017]
Full-time employee	0.077*	0.061	-0.080**	-0.011
	[0.044]	[0.037]	[0.037]	[0.015]
Part-time employee	0.072	0.037	-0.043	-0.014
	[0.052]	[0.046]	[0.046]	[0.018]
Unemployed	0.029	0.056	-0.056	-0.005
	[0.055]	[0.045]	[0.045]	[0.018]
Student	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Inactive	0.07	-0.09	0.022	0.006
	[0.092]	[0.087]	[0.077]	[0.029]
Retired	0.017	-0.083	-0.007	0.028
	[0.089]	[0.074]	[0.072]	[0.031]
Homemaker	0.04	0.008	-0.06	0.011
	[0.062]	[0.053]	[0.052]	[0.021]
Education: No qualifications	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Pre-sixteen	-0.116*	-0.104*	0.107*	0.019
	[0.066]	[0.056]	[0.064]	[0.021]
A-levels, GNVQ or college	-0.113	-0.180***	0.188***	0.009
	[0.071]	[0.062]	[0.073]	[0.023]

University (Bachelor)	-0.031	-0.089	0.121	-0.031
	[0.071]	[0.066]	[0.075]	[0.023]
Higher university degree	-0.007	-0.096	0.142**	-0.037
	[0.069]	[0.062]	[0.072]	[0.023]
House owner	0.140***	0.086***	-0.076***	-0.047***
	[0.017]	[0.017]	[0.017]	[0.007]
Log(Household income-PPP)	-0.205***	-0.077	-0.01	0.105***
	[0.065]	[0.059]	[0.061]	[0.024]
Log(Household income-PPP)2	0.054***	0.021	-0.001	-0.027***
	[0.016]	[0.015]	[0.015]	[0.006]
Log(Household income-PPP)3	-0.003***	-0.001	0.001	0.002***
	[0.001]	[0.001]	[0.001]	[0.000]
Philippines	0.185***	0.070***	-0.081***	-0.046***
	[0.024]	[0.021]	[0.024]	[0.009]
Vietnam	0.045**	0.054***	-0.067***	0.001
	[0.021]	[0.020]	[0.023]	[0.009]
% Fin. literacy effect	*-28.2%*	*-0.6%*	*50.9%*	*-72.3%*
Predicted probability	*0.4074*	*0.2136*	*0.4534*	*0.1346*
No. of Observations	3,428	3,428	3,428	3,428

Chapter 4: Price Discovery in the Bitcoin Futures and Cash Markets

4.1 Introduction

This study investigates whether the Bitcoin market price discovery is led by the futures market, and its traditionally higher concentration of informed traders, over the bitcoin trading exchanges. Building on the preceding literature on price discovery in futures and spot markets, around 75% of the new information was first impounded in the futures markets, as was already suggested in the early 1980s by Garbade and Silber (1983).

Bitcoin futures contracts were introduced to the marketplace in December 2017 as the first institutional standard cryptocurrency derivative. The contracts were launched to the market by the two globally largest futures and options exchanges, namely CME and CBOE. After half a year, the engagement in these contracts by informed or uninformed traders has been limited and volumes have remained comparatively low to-date.

Bitcoin was originally designed as a decentralised and private money payment system with founding motivations to facilitate irreversible online transactions (Nakamoto, 2008). Since then, this cryptocurrency has found popularity as a store of value. Bitcoin is claimed to be lacking the characteristics of behaving like a currency, in terms of functioning efficiently and reliably as a means of exchange, store of value or unit of account (Baur and Dimpfl, 2017). Whilst the Bitcoin can be thought to have the potential at those functions that are thought to describe a currency, it does not currently consistently act in this role due to its high price volatility. Moreover, its increase in popularity has increased the payment transaction costs. An overview of economic and technical aspects of Bitcoin and its blockchain can be viewed in studies e.g. Böhme et al. (2015), Dwyer (2015), Yermack (2013).

The analysis on Google trends and Bitcoin price research by Kristoufek (2013) suggests that whilst cryptocurrencies can be recognised as new financial instruments, they do not have underlying assets, or such related fundamentals, and subsequently will be traded on sentiment. The same study also found evidence on prevalent momentum trading on Bitcoin. Momentum trading strategies may be connected with noise trading. For example, McMillan and Speigh's (2006) study of FTSE-100 Index and futures intra-day prices suggests that noise-driven momentum trading is prevalent in rising markets, but such activity has a weaker relationship during falling markets when fundamental based trading is more pronounced. Due to the lack of tangible fundamental valuation and the ensuing downside volatility, such a trading pattern may not be suitable to describe Bitcoin trading.

Using data between 2009 and mid-2017, Baur and Dimpfl (2017) found that Bitcoin behaves neither like a traditional fiat currency nor like gold. Unlike fiat currencies, the supply of Bitcoin is exogenous (Ciaian et al. 2015). As early as the 1970s, Friedrich Hayek[42] voiced his views on libertarian private money and de-nationalisation of currencies that stand independent from central banks and monetary policies. In the same vein, in 1999, Milton Friedman[43] suggested that currencies– such as today's Bitcoin– could be facilitated by the Internet. The cryptocurrencies only properly took off after the 2007–2008 global financial crisis and the aftermath that included quantitative easing by central banks.

The bitcoin blockchain transaction system was designed to follow the economics of gold mining (Nakamoto, 2008). Like gold, bitcoin has an element of scarcity via its finite stock (Böhme et al. 2015) Moreover, procedurally, bitcoin mining requires computing and electricity resources (Garcia et al, 2014). The cost of mining new bitcoins and transaction confirmation might be the only traditional fundamental value constituents for the bitcoin pricing. By 2020, around 1800 new bitcoins are expected to be created each day, whose value will fluctuate with the popularity of the coin. The supply of the planned final amount is fixed at 21 million, after which the miners are only remunerated by transaction confirmation fees denominated in bitcoins. Currently, the price of the mining can fluctuate as the bitcoin block chain verification related mathematical problem increases or decreases in difficulty depending on the computing power available in the mining network. Since 2017, this difficulty has been increasing exponentially[44] and this impacts the economic pay-off for the miners.

Price discovery is the process in which new trading information incorporates into the efficient market price of an underlying asset (Hasbrouck, 1995, Lehmann, 2002). It can take place across various marketplaces and instruments. However, the efficient price should not be identified as the asset's fundamental value, which is based on, for example, estimating the present value of future cash flows. Price discovery, is an important attribute of the markets which are deemed fragmented, as are those for bitcoins (Hasbrouck, 1995). This methodology

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[42] F.A. Hayek interview at the University of Freiburg in 1984 https://www.youtube.com/watch?v=EYhEDxFwFRU&feature=emb_logo

[43] Milton Friedman interview by National Taxpayers Union in 1999 https://www.youtube.com/watch?v=j2mdYX1nF_Y

[44] Bitcoinity.org, which is a data provider about cryptocurrencies store information about the technical difficulty with mining.

can be applied to intra-day analysis of same basis assets traded on international exchanges(e.g., Hupperets and Menkveld,2002).

Bitcoin is a payment system whose aim was to have no centralisation of influence. However, there is evidence that individually bitcoin trading exchanges can be perceived to have a significant influence on the cryptocurrency prices (Gandal et al. 2017; Branvold et al. 2015; Moore and Christin, 2013). This would have a significant impact on the asset′s long-term price and price discovery.

In parallel studies of bitcoin cash market and futures market price discovery, Kapar, and Olmo (2019), analyse the daily prices and similarly find that futures are leading the spot market. In contrast, however, Baur and Dimpfl, (2019) find evidence of spot leading the futures through their treatment of futures prices using three-month to expiry rather than the nearest month-end expiry. This has its challenges as the longer futures contracts have very low volumes and there is also an issue with the reliability of the spot price information from the cryptocurrency exchanges. Their study does not offer a separate impact analysis of the nearer expiry futures contracts on the longer-term futures contracts or the spot prices.

Alexander and Heck (2020) study on bitcoin derivatives, including warrants and futures, and cash market during the period from 1 April 2019 to 31 January 2020 find that derivatives are leading the spot markets. This may be that the unregulated future providers can offer 100X leverage. For instance, Binance introduced Bitcoin futures in September 2020 that offer 125X leverage. These can make the instruments very efficient and impactful investment trading tools.

There are previous studies conducted on bitcoin price determining factor analysis (e.g. Zhu et al. 2017; Ciaian et al. 2015) and specifically on bitcoin exchanges price discovery (Brandvold et al. 2015; Pieters and Vivanco, 2017), before the introduction of the futures. This study contributes to the existing price discovery literature of bitcoin by providing empirical investigation on comparing the spot market and futures market with novel data. The sample is analysed at different frequencies for robustness purposes.

The rest of this study is organised as follows: Section 2 introduces the bitcoin future contracts and the bitcoin exchanges. Moreover, it situates this investigation in the existing price discovery literature. Section 3 describes the data and the empirical strategy methodologies for examining bitcoin futures and the cash market interaction. Section 4 presents and discusses the results. Finally, section 5 concludes.

4.2. Background: Bitcoin Exchanges, Futures and Price Discovery

Futures were introduced into a global bitcoin market that trades across many cash exchanges 24 hours and 7 days a week. The Bitcoin market is known for its volatility and its frictions. Price discovery methodologies provide an opportunity to compare this new financial instrument with the older innovation. The futures introduction and trading is a well-researched area in market microstructures. This may enable to make predictions of the change in the marketplace. For example, the introduction of financial futures can improve the liquidity of the underlying market (Garbade and Silber, 1983) as well as facilitate risk transfer from hedgers to speculators (Working, 1962; Silber, 1981). Further, the introduction of futures may also contribute to an immediate reduction in spot market volatility (Bologna and Cavallo, 2012).

Introduction of the futures may also have alternative influences to the spot market. Witherspoon (1993) proposed that whilst futures can dominate price discovery in the marketplace, if the initial and maintenance margins are set too high either by regulatory policy or by market practise, these can effectively contribute to the spot market bubble or crash. The introduction of futures may offer the investors, especially the smart money investors, an efficient tool for potentially shorting the overpriced market (Shiller, 2003). After the introduction of the bitcoin futures, the market saw a large price correction.

Lyons (1995) and Rosenberg and Traube (2006) compared the price determination and the trading volume sizes of the currency spot market with the futures market and noted that the futures market can exhibit a significant price discovery with a much lower volume. Similar to the currency market structure characteristics, bitcoin futures trading volume is minuscule compared to the spot market. This trading volume is around 1,000 times lower[45]. This is opposite to the gold investment market, where the futures exhibit much higher volume compared to the spot market. A potential explanation for the relatively low bitcoin futures trading may be the higher barrier to entry for retail traders compared to the bitcoin exchange trading and relative absence of institutions in the entire bitcoin marketplace to contribute to the market size.

Rosenberg and Traube (2006) have suggested that the derivatives market, in this case the futures market, can attract more informed traders. This is due to lower fees, access to leverage,

[45] CME and CBOE futures, source: Thomson Reuters and Coinmarketcap.com. January 2018.

anonymity of trading or higher speed of trade execution. Hence, they can exhibit a disproportionately much higher price determination effect relative to their lower trading volume. In addition, futures can also enable a short exposure to the market. Nonetheless, some of these features, such as leverage and asset shorting, are already available for traders at some of the bitcoin exchanges. Generally, the undiscounted bitcoin investment transaction fees, charged by cryptocurrency exchanges, are lower compared to the bitcoin futures bought through brokers.

Böhl et al. (2011) suggested that futures and spot markets′ price discovery can relate to the investor composition and to the differences between institutional and retail investor trading[46]. If the futures market trading is dominated by uninformed retail investors, it would not contribute to the price discovery of the assigned market. Whereas there is evidence on the prevalence of sophisticated traders in the bitcoin markets, e.g. those using algorithmic trading, the evidence on the wider take up by institutional investors is not as clear. Traditionally institutions are recognised for their larger transaction volumes as well as their preference for ′buy-and-hold′ strategies, as well as fundamental value investing. Institutional investors may also face further restrictions in trading bitcoin. For instance, it remains unclear how cryptocurrencies should be treated by the banks in Basel II/III regimes (Peters et al, 2014).

The bitcoin futures are priced and settled in US dollar, while the bitcoin exchanges facilitate trading bitcoin in other foreign currencies and cryptocurrencies such as Ethereum, Ripple and Litecoin. At launch, the CBOE bitcoin futures had initial margins at 44% with similar maintenance margins. These are much higher margins when compared to, for example, gold or FX futures[47]. Subsequently, these margin levels result in lower leverage than usual for futures contracts. The underlying historic market volatility contributes to the level of the margin requirement and bitcoin has been extraordinarily volatile compared to other assets or currencies (Kasper, 2017). This volatility may have been further fuelled by leveraged purchases with credit cards[48] and by up to 15-time leverage[49] on exchanges. There are also exchanges that offer derivatives on bitcoin, but there have been difficulties with clearing these trades.

[46] This study considers an institutional investor as an entity that manages funds for i.e. a pension fund or an insurance company. Retail trading in Bitcoin, on the other hand, might involve mobile phone interface with a Bitcoin exchange with access to very limited trading information.

[47] For instance, on 7 March 2018, CME offered Gold futures with 100 troy ounce contracts with a maintenance margin of USD3500. 100 troy ounce of gold was reported to be USD1330.0 making the leverage 38 times.

[48] Bitcoin Ban Expands Across Credit Cards as Big U.S. Banks Recoil, Bloomberg, 2 February 2018.

[49] Bitflyer Lighting FX, accessed on 30 January 2018.

A CBOE Futures contract unit equals one bitcoin. The CBOE exchange′s typical trading hours apply with only a partial weekend trading and 15 minutes closing period for settlements during the weekdays. The contract is priced off on an auction at 3pm Central Time on a Gemini cryptocurrency exchange. There is a discretionary 20% daily price fluctuation trading cap. On the whole, the CBOE futures are quite similar to the CME futures. However, they have differentiated contract sizes and strike price calculation mechanisms. Namely, CME′s minimum contract size is five bitcoins and their contract is priced by a CME bitcoin Reference Rate constructed with a few bitcoin exchanges; namely GDAX, Kraken, itBIT, Bitstamp and Lakebit exchanges during 3–4 pm trading (Painem and Knottenbelt, 2016).. It appears that CBOE is seeking to offer higher technologically advanced trading and appealing to both retail and institutional traders, while CME pursues to appeal to institutional clientele. The CME bitcoin futures trade at higher volumes.

The bitcoin futures market has natural hedgers, who are the bitcoin miners and transaction verifiers. Currently, a single bitcoin block mining compensates a miner with 12.5 bitcoins as well as with the transaction fees, which are also denominated in bitcoins. A new block with thousands of transactions is mined every 10 minutes. In total, up to 1800 new bitcoins are produced each day until the estimated 2020. After this, the number of bitcoin compensation to miners will halve further and represent 6.25 bitcoins per a block. Only 21m bitcoin tokens can be mined, after which the miners will be compensated only with transaction fees.

As the current bitcoin futures are cash-settled, miners who might seek to participate in hedging their long-term mining activities, and their bitcoin price exposure, would be required to exchange the mined bitcoins or transactions fees to cash at the bitcoin exchanges before settling the futures trades or margins with the broker. This process further makes the miners reliant on the bitcoin exchanges, and the process is cumbersome even without considering the futures′ high margin premiums.

Considering that CME and CBOE had their own base initial and maintenance margins, the brokers, through which the hedgers act, can demand even higher requirements. These high margins could be possibly avoided if the futures contracts were also directly settled by bitcoin. This would additionally provide a direct portfolio diversification benefit for speculators who are the counterparties for these trades.

In addition to selecting the preferred trading instruments, access to the price information can also influence traders′ trading decisions. While the bid-and-ask order book information is readily available to traders at the bitcoin exchanges, there are higher barriers when accessing live information on bitcoin futures bid–ask quotes. This information can be accessed through a broker or the futures exchange at an additional fee. Subsequently, this distinct access to data could create an informational advantage (Ito et al. 1998). Nevertheless, algorithmic trading in the bitcoin markets and the opportunity to arbitrage, as well as enhanced monitoring and trading technologies, can reduce the price differences between the marketplaces (Hendershott and Riordan, 2013). For efficient marketplace, the arbitrage conditions would need to be present so that the prices of different instruments for the same underlying would not diverge (Hasbrouck, 1995). The price quotes of the same underlying in the various market place are assumed to converge in the long run (de Jong et al., 2001).

The significance of trading information sourcing is also supported by price discovery studies by Tse, et al. (2006) and Hasbrouck (2003). Tse, et al. (2006) compared Euro and Yen FX traded on the futures electronic markets, futures trading floor and electronic retail spot market. They found that the traders favoured electronic marketplaces for their immediate, anonymous trading capacity and transparent pricing. Therefore, the futures and retail spot markets led price discovery over the futures physically traded in the pits. As with the trading pit and with the bank interdealer FX platforms, where most trading took place, these marketplaces offered simultaneously different exchange prices. This would suggest a frictional marketplace where the best pricing information leads.

Hasbrouck′s (2003) price discovery study on US Equity Market Indices focused on the relationship between the E-mini futures that are traded electronically, traditional pit traded futures and exchange traded funds (EFTs). The study discovered that E-mini futures, which were available for S&P 500, dominated with over 90% of the price discovery. This is with making an allowance for pit traded futures′ lower fees, higher cash nominated volumes and open interest. The E-minis trading was shown to have an informational advantage and enhanced price transparency by means of disclosing the real time bids, asks and market depths.

While the contemporaneous differences in the exchanges′ bitcoin returns can indicate arbitrage opportunities[50], there are considerations over the fees, liquidity and exchange access (Kroeger and Sarkar, 2016). Previous studies have carried out a case for arbitrage trading opportunities across various bitcoin exchanges due to continuing market frictions (e.g Kristoufek, 2015; Pieters and Vivanco, 2017; Halaburda and Gandal, 2014). This is also backed

[50] E.g. Bitcoinity Bitcoin Arbitrage Chart

by the existence of traders employing arbitrage strategies in bitcoin markets. Understanding of the major and satellite markets can be important for fully grasping the market dynamics (Garbade and Silber, 1983). Furthermore, the bitcoin prices can vary between the larger and smaller regional markets due to volume differences and market access which contribute to a frictional marketplace.

Considering that bitcoin exchanges were only recently established, this can coincide with higher predisposal to operational difficulties such as downtimes due to high volume of users[51], denial of service attacks, or hacking. An additional benefit for trading futures has been demonstrated to be that bitcoin exchanges have also been subject to suspicious trading activity or theft on certain occasions (Gandal et al., 2017; Moore and Christin, 2013). There have also been instances of exchanges founded on purely fraudulent intent (Vasek and Moore, 2015). In addition to the exchanges, there are claims that other cryptocurrencies facilitated by lax regulation have had a large influence on the bitcoin price (Griffin and Shams, 2020).

Brandvold et al. (2015) found that larger exchanges by trading volume led price discovery and smaller exchanges followed with a lag with especially Mt. Gox demonstrating a dominating information share. Before Mt. Gox exchange was forced to shut down, the traders customarily paid premium on their bitcoins due to fraudulent trading activity, and this had a significant impact on the bitcoin price rise across the whole market (Gandal et al. 2017). Noting this, large price deviations between a single and groups of exchanges could help to identify enhanced risk (Brandvold et al. 2015). These price distortions can be substantial in size or duration, as was evidenced in the example of the Mt. Gox collapse.

At the outset, bitcoin market enjoyed a low supervisory regime which may have encouraged exchanges in engaging activities that contributed to further volatility, instead of only contributing to the price discovery through their microstructure specifications in a frictional marketplace. The presumption is that the bitcoin futures marketplace is not only more informative, but also the futures are more efficient financial instruments compared to the cash market that is largely unregulated, having varied quality exchanges and driven by retail investors.

[51] Twitter: history of Bitcoin exchange downtimes may be seen on the Twitter, where users of Bitcoin exchanges can share and seek information from peers about exchange downtimes and possibly interact with exchanges themselves.

4.3 Data and methodology

Figure 4.1 depicts volatile but also cointegrated 1-minute time series of spot-futures markets. To measure this relationship, Johansen co-integration, Granger causality and VECM methodologies with also Information Share (IS) and Component Share (CS) tests are applied.

Figure 4.1 Bitcoin spot and futures market 1-minute frequency

Red: Represents the CBOE Bitcoin Futures Prices. **Blue:** Represents the Spot Market Index Bitcoin Prices. 1-minute level data from Coindesk. Translated from the US dollar. Sample data is captured between 2017.12.13 to 2018.05.16 (UCT).

Following Tse et al. (2006) specified *relativeness* of price discovery acknowledging that the causes of the price changes may not be initiated in these marketplaces. Therefore, the study will not endeavour to research areas of macro factor analysis and cross-asset valuation.

This study examines the price discovery relationship between spot and futures markets during the first 5 months of trading between 13 December 2017 and 16 May 2018. Spot market is represented by the USD denominated bitcoin Coindesk simple unweighted average of minute-level frequency index. This is generated via four main bitcoin exchanges' mid-price [52].

[52] Coindesk Bitcoin Price Index simple average weighted constituents of immediate bid and offer spread are Bitstamp, Coinbase/GDAX, itBit, Bitfinex as of 31st May 2018. The time frequency is 1-minute UTC time.

Then, the futures mid-price order book data of the CBOE bitcoin futures is sampled.[53] The preference on the bid-and-ask data, or mid-price, draws on the possibility of being able to trade at those prices on that captioned time.

When constructing the CBOE bitcoin futures′ continuing time series with mid-book prices and noting the various contract expiry dates, only the 1-month duration contracts to their nearest settlement were selected for the time series. At the settlement, the prices were rolled over on to the next month contracts. These 1-month contracts significantly dominate the open interest volume over other contracts. The CBOE bitcoin futures data were selected for this analysis over the CME bitcoin trading data, even considering the CME bitcoin contracts′ higher trading volume, due to CBOE bitcoin futures′ earlier launch by a week. When there are no available trades and simultaneously reported bid–ask quotes, these observations are omitted, as are the periods when the futures markets are closed for trading[54]. Altogether 575,615 (long) CBOE bitcoin Futures contracts were traded on 403,907 separate occasions during the sample period. The sample data order book shows maximum spread of USD350 with minimum of USD0 with an average spread of USD22 with USD18 of standard deviation. In the CBOE bitcoin futures sample data, the average contract order size is 1.4 with 1.1 standard deviation.

[53] Data Availability Statement – data subject to third party restrictions: Futures data are available at https://www.cboe.com with the permission of Cboe Global Markets, Inc.

[54] CBOE Bitcoin futures trading hours are 3:30 p.m. to 3:15 p.m. CT on Mondays and 8:30 a.m. to 3:15 p.m. Tuesday through Friday. Weekend related extended hours are 5 p.m. Sunday to 8:30 a.m. Monday.

Irregular quoting can be an effect of absence of volume and liquidity, as implied by Andersen (2000) in an examination of high frequency time series data.[55] With electronic trading, this requirement is even more pronounced. At the time of the study, the bitcoin futures remain a relatively thinly traded instrument, compared to the higher volume bitcoin exchange trading. To overcome this limitation, the intra-day data will be tested on a variety of frequencies. The price discovery is tested at 1-minute, 5-minute, 15-minute, 30-minute, 1-hour and 1-day frequencies. This also offers benefits with treating the random walk components at different frequencies as well as the white noise. Whilst there is 1-second level data available for the bitcoin spot market index, the zero median result at the highest frequencies in *Table 3.1* points out the infrequency of change in the futures pricing quote in the median return row. Further descriptive statistics are provided before the methodology overview.

The average prices for the spot and futures are roughly similar in the comparable samples. For instance, at 1-minute data frequency level that has 78,720 observations, the spot market′s mean price is USD10,453 with USD2,775 of standard deviation compared to the futures market equivalents at USD10,479 and USD2,833. For the daily data sample, the spot market′s mean price is USD10,432 with USD2,910 standard deviation and similarly USD10,458 with USD 2,959 for the futures.

Table 4.1 describes the bitcoin spot and futures series′ return statistics. The average return is negative for the spots and futures in all of the frequency samples. The spot market′s daily mean return is equal to -0.6% with a standard deviation of 6.3%. The results are similar to the futures market with daily average of -0.7% and 6% of standard deviation. The spot and futures returns are positively skewed for the intra-day data. The excess kurtosis for spot and futures intra-day samples and for the daily spot market sample, suggests leptokurtic distribution with higher amount of return observations in the tails. The range of daily returns for spot market is from -24.4% to 13.1%, while the range for futures returns is lower at -17.7% to 13.7%.

[55] The time stamp matching is important as Garbade and Silber (1983) find. Daily cut off pricing point can either make the market appear more dominant with only 30 minutes difference in the timing.

Table 4.1

Summary statistics: Coindesk Bitcoin Index (Spot) and CBOE Futures (Futures) Returns. Returns were transformed from prices in the sample data during the time period from 2017.12.13 to 2018.05.16 (UCT).

	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Returns	1 minute		5 minutes		15 minutes		30 minutes		1 hour		1 day	
Min (%)	-9.2%	-9.1%	-8.9%	-9.4%	-8.9%	-9.3%	-8.7%	-9.3%	-11.7%	-10.2%	-24.4%	-17.7%
1% (returns %)	-0.6%	-0.8%	-1.3%	-1.4%	-2.3%	-2.3%	-3.4%	-3.5%	-4.4%	-4.5%	-19.5%	-13.4%
5% (returns %)	-0.3%	-0.4%	-0.7%	-0.7%	-1.2%	-1.2%	-1.6%	-1.7%	-2.4%	-2.4%	-11.4%	-11.1%
10% (returns %)	-0.2%	-0.3%	-0.4%	-0.5%	-0.8%	-0.8%	-1.1%	-1.1%	-1.7%	-1.7%	-8.8%	-8.6%
Median (returns %)	8.5e-06%	0%	1.8e-06%	0%	1.6e-05%	0%	-3.9e-05%	0%	6.8e-05%	0%	0.1%	-0.2%
90% (returns %)	0.2%	0.3%	0.4%	0.4%	0.7%	0.7%	1.0%	1.0%	1.4%	1.5%	6.1%	6.3%
95% (returns %)	0.3%	0.4%	0.6%	0.6%	1.1%	1.1%	1.6%	1.6%	2.3%	2.2%	9.7%	10.2%
99% (returns %)	0.6%	0.8%	1.3%	1.4%	2.2%	2.3%	3.1%	3.1%	4.4%	4.2%	12.7%	13.4%
Max (returns %)	13.0%	13.0%	12.8%	13.3%	12.9%	13.7%	12.5%	13.7%	12.7%	13.7%	13.1%	13.7%
Mean (returns %)	-8.9e-06%	-9.6e-06%	-2.9e-05%	-3.1e-05%	-8.2e-05%	-8.5e-05%	-0.016%	-0.017%	-0.03%	-0.03%	-0.6%	-0.7%
SD (returns %)	0.23%	0.27%	0.5%	0.5%	0.8%	0.8%	1.1%	1.1%	1.6%	1.6%	6.3%	6.0%
Skewness	2.2	1.5	1.0	1.0	0.8	0.6	0.5	0.4	0.3	0.3	-0.7	-0.1
Excess Kurtosis	219	108	49	45	19.3	20.1	13.1	13.1	8.6	8.7	1.4	0.1
No. of Observations	*78,720*	*78,720*	*24,928*	*24,928*	*8,963*	*8,963*	*4,567*	*4,567*	*2,293*	*2,293*	*103*	*103*

Table 4.2 describes the increasing spot-futures return correlation at lower frequencies. Namely, the minute level 0.67 correlation increases to 0.86 for 1-hour and finally to 0.90 daily correlation. Noteworthy is the standard deviation of the 1-minute level return sample is higher by 0.05% and that the spot market has a remarkably higher excess kurtosis at 1-minute level implying for more outliers.

Table 4.2
Correlations of CBOE Futures and Coindesk Index Returns between time period between 2017.12.13 to 2018.05.16 (UCT).

	1 min	5 min	15 min	30 min	1 hour	1 day
Correlation	0.67	0.71	0.80	0.83	0.86	0.90
No. of Observations	*78,720*	*24,928*	*8,963*	*4,567*	*2,293*	*103*

4.3.1 Cointegration of the price series

Prior to identifying a significant lead–lag relationship between the futures and spot markets, first cointegration must be determined. Cointegration measurement involves identification of the time series′ long run relationship and the series′ sensitivity to the estimated efficient price. The Johansen′s cointegration test procedure is applied to the spot and futures prices at the various frequencies. In preparation, each of the series′ logarithmic prices′ non-stationarity are examined with augmented Dickey–Fuller unit root (ADF) test. ADF test can be described as follows:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \delta \Delta Y_{t-1} + \delta_2 \Delta Y_{t-2} + + \delta_n \Delta Y_{t-N} \varepsilon_t \quad (1)$$

where: ΔY is the change at the bitcoin index and bitcoin futures log prices, α is a constant and β the coefficient of the long-term trend. If β = 0, the sample can be identified as non-stationary. When determining the lags for all the tests in this study, the most parsimonious model specification used will be that identified by either Akaike (AIC), Hannan–Quinn (HQ) or Bayesian (BIC) information criteria. The ADF test identifies the examined series log prices non-stationary at all frequencies at 1% critical value level.

The Johansen test utilises a maximum likelihood estimator for a cointegrated system with Gaussian errors. According to Johansen (1991), the starting point is the transformation of the Vector Autoregression model (VAR) of two non-stationary time series into a Vector Error Correction Model (VECM)[56]. This can be written as:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_j \, \Delta Y_{tk} + \Pi \, Y_{t-1} + \varepsilon_t \quad (2)$$

where: ΔYt is the first difference of the assessed two non-stationary variables. Γ is the $n \times r$ matrix of coefficients and Π represents the coefficient matrix; k denotes the lag length and μ is a constant term which will be ignored in this model. This study uses the trace model specification of the Johansen test owning to its more powerful estimation capability in smaller data samples, compared to the maximum eigenvalue test. The daily data has only 104 full day observations. For the intra-day data, and their higher observation number, using either Johansen test specification would not induce much concern (Lütkepohl et al., 2001). Formulating the trace test's null hypothesis of no co-integrating vectors (H_0: $r = 0$) against the alternative hypothesis of one co-integrating vector (H_1: $r > 0$), the test can be expressed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln\,(1 - \lambda_i) \quad (3)$$

where: r is the number of cointegrating relationships between the variables. As in this case, the cointegration of the bivariate series with 1 relationship would imply one unit root. Here, T is the sample size. λ_i denotes the eigenvalues of matrix Π. If eigenvalues up to i are $\lambda = 0$, then the rank of Π is zero and this is resulting to no cointegrating vectors. In this manner, the estimated eigenvalues of λ_o, λ_1, ... λ_{n-1} would need to be significantly larger than the critical values for the rejection of the null hypothesis. The critical values are taken from Osterwald-Lenum (1992). As shown in *Table 3*, the null hypothesis of the zero cointegrating relationships, (H_0: $r = 0$), can be rejected at all tested frequencies at the 1% critical value level, favouring the alternative hypothesis of 1 cointegrating relationship, (H_1: $r > 0$).

[56] The study utilizes R for analysis. For more on R model implementations see Pfaff (2008).

Table 4.3
Johansen procedure for co-integration test on logarithmic prices. The critical values applied for the test statistics are from Osterwald-Lenum (1992). Asterisks denote the following levels of significance: *** p<0.01, ** p<0.05 , * p<0.1. When determining the lags for the tests, the most parsimonious model specification used will be that identified by Akaike (AIC), Hannah-Quinn or Bayesian information criteria.

	1 min	5 min	15 min	30 min	1 hour	1 day
Result	Co-integrated	Co-integrated	Co-integrated	Co-integrated	Co-integrated	Co-integrated
Trace Test						
r=0	144.5 ***	67.1***	63.2***	63.2***	66.4***	45.3***
Critical value 0.05 = 17.95, Critical Value 0.01 = 23.52						
r=>1	5.3	4.5	5.6	4.30	5.2	3.9
Critical value 0.05 = 8.18, Critical Value 0.01 = 11.65						
Lags	*14*	*8*	*8*	*7*	*5*	*2*
No. of Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

4.3.2 VAR/VECM processes

4.3.2.1 VAR model specification for Granger causality test

To assess the direction of causality, as well as the instances of robustness, the Granger causality test is applied to the bivariate time series. As the Granger causality model requires stationarity, the price series are accordingly transformed into returns. The ADF unit root test is applied for the series stationarity assessment. At all frequencies, the results show statistically significant stationarity at the 1% critical value level.

The Granger causality test involves identifying whether the lagged information of a variable Y provides any information about a variable X with also the lagged X components. The lags for this bivariate VAR process are determined with the shortest model, as identified by either AIC, HQ or BIC. To examine this, the F-test is applied to the unrestricted equation and restricted equation by ordinary least squares. Implying that Y_t does not Granger cause X_t, and in reverse, if $\beta = 0$, i.e: $H_o = \beta_1 = \beta_2 = \cdots = \beta_k = 0$. Should the F-test be greater than the critical value, then the null hypothesis of Y not Granger causing X, or in the reverse variable order, can be rejected.

4.3.2.2 Price discovery models

To measure price discovery as share of marketplaces' contribution of new information, this study employs the information share model by Joel Hasbrouck (1995) and the component share model by Gonzalo and Granger (1995). These are both widely used price discovery models and are constructed on the components of Vector Error Correlation Model (VECM). As already confirmed under the Johansen cointegration test preparation, the VECM also requires non-stationary log prices. These price discovery models assume a single efficient market price, or long-term price equilibrium. Basing on the VECM short-term and long-term relationship components, these models can provide measurable insight into the futures and spot markets' lead–lag relationship.

The VECM model specification can be written as, in (4) where the change in the efficient price (ΔP_t) can be written:

$$\Delta P_t = \alpha(\beta' P_{t-1} - E(\beta' P_{t-1})) + \sum_{i=1}^{k} \Gamma_i \Delta P_{t-i} + \varepsilon_t \quad (4)$$

and:

$$\Pi = \alpha[\beta' P_{t-1} - E(\beta' P_{t-1})] \quad (5)$$

where: α is the error correction vector, containing the coefficients associated with the speed of adjustment of each price series to deviations from the equilibrium. The column β contains cointegrating vectors, or the long run coefficients. Considering that there are only two variables, here, Γ is a 2×2 common factor coefficient vector matrix. e_t is a 2×1 non-diagonal covariance matrix Ω of the residuals with a mean of zero. The matrix $\Pi = \alpha\beta'$ is of reduced rank in identifying co-integration. The model's common factor, or the efficient price, can be explained as the permanent component of I(1) co-integrated of vectors.

4.3.2.3 Information share

The information share (IS) model by Hasbrouck (1995) measures the proportion of the efficient price variance which can be attributed to each market's innovations. IS model incorporates the covariance matrix of innovations, the proportion of the random-walk variance that is attributed to the innovations in the spot or futures market price. Similar to the Johansen test (1991) before noting the futures and cash prices' integration of order I (1) with a random walk and the price changes, the VECM model can be transformed into a vector moving average of prices changes. Applying this model for a bivariate log prices:

$$\Delta P_t = \Psi(L)\varepsilon_t = \varepsilon_t + \Psi_1\varepsilon_{t-1} \ \Psi_2\varepsilon_{t-1} \quad (6)$$

where ΔP_t is change in the efficient price, $\psi(L)$ is a polynomial lag operator and ε_t the error term. Noting the Beverage-Nelson decomposition of the efficient price into permanent ($\Psi(1)\varepsilon_t\sum_{s=1}^{t}\varepsilon_s$) and transitory ($\Psi^*(L)\varepsilon_t$) components:

$$P_t = \Psi^*(L)\varepsilon_{t+} \Psi(1)\varepsilon_t\sum_{s=1}^{t}\varepsilon_s \quad (7)$$

The cumulate impacts of ε_t innovations are contained in the matrix $\psi(1)$ that measures the long-term impacts. Considering the Engle–Granger (1987) VECM representation theorem, the matrix $\Psi(1)$ shows the following:

$$\beta'\Psi(1) = 0 \quad and \quad \Psi(1)\alpha = 0 \quad (8)$$

and, further providing that:

$$\beta = (1, \text{-}1)' \qquad (9)$$

The rows of $\Psi(1)$ are identical as in Hasbrouck (1995). Be $\psi = (\psi_1, \psi_2)$ the each common row vector of $\Psi(1)$. Defining the permanent innovation $\psi'\varepsilon_t$ as the long-run impacts of innovations on each price series as below:

$$\psi'\varepsilon_t = \psi_1\varepsilon_1,\mathrm{t} + \psi_1\varepsilon_2,\mathrm{t} \quad (10)$$

If Ω is diagonal, and the innovations are independent, the market i's (1 and 2) information share can be defined as below:

$$IS_i = \frac{\psi_i^2\,\Omega_i^2}{\psi\Omega\,\psi^T}, i = 1, 2 \quad (11)$$

$\psi\Omega\psi^T$ is the variance of $\psi\varepsilon_t$. If Σ is non-diagonal and would not provide a unique solution, the market i's information share can be solved by applying Cholesky factorisation. Information share model is transformed into:

$$IS_i = \frac{([\psi F]_i)^2}{\psi\Omega\psi'}, i = 1, 2 \quad (12)$$

The F is the Cholesky decomposition of a lower triangular matrix of FF' = Ω. $[\psi F]_i$ is the *i* element of the matrix row. The IS result will depend on the ordering of the price variables, and as well as the general representations solved by Cholesky factorisation as upper and lower bounds. This in effect maximises the information share of market 1 whilst minimising market

2's share. Therefore, in this bivariate system, the marketplaces' information shares both require a combination of computed upper and lower bounds. As below:

$$IS_1 = \frac{(\psi_1\sigma_1 + \psi_2 p\sigma_2)^2}{(\psi_1\sigma_1 + \psi_2 p\sigma_2)^2 + \psi_2^2\sigma_2^2(1-p^2)}, IS_2 = \frac{\psi_2^2\,\sigma_2^2(1-p^2)}{(\psi_1\sigma_1 + \psi_2 p\sigma_2)^2 + \psi_2^2\sigma_2^2(1-p^2)} \quad (13)$$

IS_1 and IS_2 represents the upper and lower bound of the marketplace. The average of upper and lower bound results of each market can be calculated as an estimation of price discovery measure (Baillie et al. 2002).

4.3.2.4 Component share

The component share (CS) model was introduced by Gonzalo and Granger (1995) with original examples sourced from macro finance and the purposes of researching long-running and co-integrated time series. Similarly to the IS, the CS model's common factor, or the efficient price, can be explained as the permanent component of I(1) co-integrated of vectors. However, the CS model differs by measuring the contribution to the efficient price from each market, where the contribution is defined as a function of the error correction coefficients of the marketplaces. The transitory components are not assumed to influence the common factor in the short run. Intuitively, this model places less price discovery share to a market where transitory activity is more prevalent. The CS model can be written as such:

$$P_t = f_t + G_t \qquad (14)$$

$$f_t = \Gamma^T P_t = (\alpha^T{}_\perp \beta_\perp)^{-1}\, \alpha^T{}_\perp\, P_t \qquad (15)$$

$$\alpha_0 \perp \alpha = 0 \quad \text{and} \quad \beta_0 \perp \beta = 0 \quad (16)$$

$$\Gamma^T = (\Gamma_1, \Gamma_2)^T = \left(\frac{\alpha_2}{\alpha_2 - \alpha_1}, \frac{\alpha_1}{\alpha_1 - \alpha_2}\right)^T, \ \mathrm{i} = 1, 2 \quad (17)$$

Where: P_t is cointegrated prices and is composed of f_t, the long running component and G_t, the transitory component that has no permanent impact on the long run. $\alpha\perp$ is a vector orthogonal to the error correction coefficients matrix α for the market 1 and 2. α as well as β correspond to the VECM components. Γ^T is the common factor coefficient vector of sample T and which total sum of its components is normalised to be equal to 1 (Harris et al., 2002).

The examination on price discovery measurement models by Ballie et al. (2002) assessed whether the price discovery should not only consider error correction processes but also correlations of VECM residuals, and suggested that inclusion of the latter in the model might offer more complete interpretations. In this manner, the information share test is assumed to be more comprehensive.

4.3.2.5 VAR/ VECM process measurement limitations and robustness

The tests were performed at different frequencies for robustness purposes due to the possible auto-correlation features of intra-day data and also for bitcoin's price volatility against the US dollar. The expectation is that when using intra-day data, the samples will exhibit positive autocorrelation in the residuals. Further the Durbin–Watson test is applied to log prices to measure the linear regression before lags are applied in preparation for the VECM test. The Durbin–Watson test can be facilitated to identify the prevalence of continuing price increases or decreases which could be related to momentum investing. Momentum trading would need to be separated from liquidity induced price increase and decrease moves as not all momentum trading can be explained by irrational trading or trading frictions as suggested by an equity return research (Johnson, 2002).

The value of the Durbin–Watson test lies between the range of 0 and 4. Small values of the estimations indicate that the consecutive error terms are positively correlated. The test estimations as shown in *Table 4.4* showed positive autocorrelation on the higher frequency intra-day data on the time series′ co-integration. A result between the 0 and 1 value can be identified as noting positive autocorrelation in the series as a rule-of-thumb. This was the range in which all the tested intra-day results were estimated to belong. To make the log prices applicable for the VEC model, the lags were defined with AIC, HQ and BIC methods.

Table 4.4

Durbin–Watson Test Statistics for the Linear Regression of log prices. Asterisks denote the following levels of significance: *** p<0.01, ** p<0.5 , * p<0.1. P-values are in the parentheses.

	1 min	5 min	15 min	30 min	1 hour	1 day
Test statistics	0.10***	0.27***	0.45***	0.64***	0.90***	1.85
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.193)
Lags to be applied	*14*	*8*	*7*	*7*	*5*	*2*
No. of Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

4.4. The empirical results and estimations

Bitcoin spot and futures pertain to the same underlying asset and were correspondingly identified to be cointegrated by applying the Johansen Cointegration Trace test to the time series′ logarithmic intra-day prices at different frequencies. At the 1-minute frequency, the CBOE futures and spot prices show Johansen trace statistics of 144.5 with 5% critical values of 17.95 and 1% critical values of 23.5. This makes the researched bivariate series I(1) co-integrated at all the tested frequencies.

To research this relationship in detail with regards to predicting the move of a variable from another variable move, the Granger causality test was employed onto the transformed returns. The test results that can be seen in *Table 4.5* demonstrate significant p-value statistics of the futures Granger causing spot returns at all frequencies and for spot market Granger causing the futures at the 1-minute frequency level. The lower frequencies do not reveal significant results of the spot index Granger causing the futures returns. The Granger causality test shows that the relationship cannot be ascertained to be bidirectional at lower frequencies while futures exhibit Granger causing spot markets at all tested frequencies.

Table 4.5

Granger causality – null hypothesis p-value – returns. When determining the lags for the tests, the most parsimonious model specification will be used by identified by either Akaike (AIC), Hannah-Quinn or Bayesian information criteria. Time period 2017.12.13 to 2018.05.16 (UCT).

	1 min	5 min	15 min	30 min	1 hour	1 day
Spot does not Granger cause Futures	0.000	0.300	0.270	0.106	0.385	0.259
Futures does not Granger cause Spot	0.000	0.000	0.000	0.000	0.000	0.000
Lags	*14*	*9*	*8*	*7*	*5*	*2*
Observations	*78,720*	*24,928*	*8,963*	*4,567*	*2,293*	*103*

The VECM is applied to non-stationary log prices for the bitcoin index and CBOE futures at different frequencies. The results in Table 4.6 show an error correction coefficient that is significant at 1% p-value level for the futures impacting the index prices in all the frequency samples. The VECM results show insignificant error correction test results of futures correcting towards the efficient price at all frequencies. In contrast the spot market was found to be correcting toward the efficient price with statistical significance on all frequencies. Spot market is also shown to be downwardly correcting to the efficient price.

Table 4.6

Vector Error Correction Model Results – log prices. Notes: Asterisks denote the following levels of significance: *** p<0.01, ** p<0.5 , * p<0.1. P-values are in the parentheses.

	1 min	5 min	15 min	30 min	1 hour	1 day
Error Correction Term						
SPOT	-0.008***	-0.030***	-0.046***	-0.099***	-0.191***	-0.808***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.807)
FUTURES	0.002	0.038	-0.000	-0.016	-0.038	0.193
	(0.283)	(0.713)	(0.989)	(0.545)	(0.454)	(0.548)
Cointegration Relations	0.989	0.989	0.991	0.991	0.990	1.010
Correlation of Residuals	0.753	0.806	0.866	0.887	0.907	0.899
Residual Standard Error						
SPOT	0.002	0.004	0.007	0.010	0.015	0.056
FUTURES	0.003	0.005	0.008	0.011	0.016	0.058
% Adjusted R^2						
SPOT	20.5%	19.9%	13.5%	12.3%	11.9%	22.8%
FUTURES	0.3%	2.1%	5.1%	0.5%	0.6%	6.7%
Lags	*14*	*8*	*7*	*7*	*5*	*2*
Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

.

Both IS and CS models measure each market's price discovery contribution as a share of the total 100% price formation. *Table 4.7* shows the results of these models. At 1-minute level frequency, 66.6% of price discovery is generated from the futures market as measured by the averaged IS model and 82.3% as measured by CS model. At 1-hour frequency level, the IS result is 62% and the CS result is 84.2% of the price discovery share for the futures market. The futures dominate the price discovery at all sampled frequencies with a range from 56% to 73% with information share test and respectively 82% to 95% with component share test. The results from Granger causality and VECM corroborate the information share and component share model estimations with supporting that the futures are leading the spot market in price discovery.

Table 4.7

Information share and component share estimations – log prices. Notes: The information share (IS) model is by Hasbrouck (1995). The component share (CS) model is by Gonzalo and Granger (1995). When determining the lags for the tests, the most parsimonious model specification will be used by identified by either Akaike, Hannah-Quinn or Bayesian information criteria.

	1 min	5 min	15 min	30 min	1 hour	1 day
IS upper bound						
FUTURES	34.1%	31.6%	23.3%	27.7%	24.8%	13.1%
INDEX	65.9%	68.4%	76.7%	72.6%	75.2%	86.9%
IS lower bound						
FUTURES	99.1%	99.9%	99.9%	99.5%	99.2%	99.4%
INDEX	0.9%	0.1%	0.1%	0.5%	0.8%	0.6%
Average IS						
FUTURES	66.6%	65.8%	73.3%	63.4%	62.0%	56.3%
INDEX	33.4%	34.2%	26.7%	36.6%	38.0%	43.7%
Component share						
FUTURES	82.3%	93.1%	95.0%	87.6%	84.2%	81.6%
INDEX	17.7%	6.9%	5.0%	12.4%	15.8%	18.4%
Lag	*14*	*8*	*8*	*7*	*5*	*2*
Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

4.5 Concluding remarks

The analysis of the bitcoin spot-futures information share and component share test results suggest that the bitcoin futures are leading the price discovery. These findings are also corroborated by the results from VAR and VECM specified processes. The results support the majority of research findings of futures' dominance in price discovery. As the component share model does not consider the transitory element, the higher information share result may imply more prevalent noise trading in the spot market. Due to the comparatively low volumes in the futures trading of this asset, this will not support wider participation among institutional traders in the whole marketplace. Nevertheless, even with the unusually high margins, the bitcoin futures provide traders a more robust instrument and more efficient information for trading in the developing but frictional bitcoin marketplace. The challenge for the bitcoin market is to improve the undeveloped best practises among the bitcoin cash exchanges that largely remain unregulated and mainly retail focused. Furthermore, the availability of leverage by using derivatives on unregulated exchanges is a challenge. The regulated futures markets have two genuine market counterparties to go long or short a futures contract through clearing houses, whereas it is not certain if the unregulated exchanges this holds for their derivate offering where they can take up to 100 times leveraged positions to either direction.

Chapter 5: The Role of Technology and Network Externalities in the Long-Term Performance of ICOs

"Business has only two functions – marketing and innovation"

– Milan Kundera

5.1. Introduction

Initial Coin Offerings (ICOs) confer transferable ownership rights in form of tokens (i.e. cryptocurrencies, digital assets or cryptoassets) to the owner. ICOs are a new fundraising instrument used to finance technological innovation against a digital voucher or receipt. They diffuse the ownership of claim for a digital good. The OECD (2019a) defines the ICOs as activity in "*creation of digital tokens by small companies to investors, in exchange for fiat currency or first-generation dominant cryptocurrencies*". They also propose that network effects are an important aspect of the economic value that is created by ICOs (OECD, 2019b). This study focuses to inspect this phenomenon.

Technology and Networks words, which can be viewed in figure 1 in appendix 2, present the third and fourth most frequent words used in the sample's ICO descriptions that were drawn from the ICObench database. Moreover. Blockchain, Platform and Decentralized are the most frequent words[57]. The introductions were often told in the present, nevertheless, in the majority of the cases, the ICOs product or service were not developed by the time of the ICO fundraising.

The largely unregulated nature of ICOs is said to have resulted in several fraudulent or poorly conceived offerings. Many ICOs are being described as 'frauds' (e.g. Dowlat, 2018; Shifflett and Jones, 2018). But also the business failures can arise through poorly conceived business concepts and practises. This study was planned to inspect fraud in ICOs, but no empirical evidence could have been gleaned from the data to differentiate fraud from a business failure without researching the legal proceedings manually. Fraud and business failure can both end up in capital loss for investor. There is a study that looks at fraud in ICOs through legal proceedings and find a low number of these court judgements (Liebau & Schueffel, 2019).

[57] Further word frequency count was applied to the job titles between genders. These can be inspected in the figures 2 and 3.

Nevertheless, absence of the requirement for company legal filings and the provision of historic financial statements, along with third-party verification, often induce fallibility of self-reported information, which is to be provided to ICO investors. Hence, this study emphasizes on the determinants of the longer-term success of ICOs. This is more indicative of project quality as the market learns with time, compared to static measures of success in the previous literature, e.g. the amount of assets raised. The inquiry into the informational efficiency of the primary and secondary markets for ICO value determination is of scholarly and practical importance. In the extant literature, the determination of value for crypto assets have been considered to be challenging (Giudici et al 2020; Chimienti et al 2019; Baur et al. 2018). The network effects in ICOs can be empirically measured and this is supportive that the ICO organisations create value through technical innovation.

Due to the novelty of ICOs, most of the recent studies of ICO organisations use the volume of the total assets raised as the main proxy of their success (e.g. Boreiko and Risteski, 2020; Campino et al., 2020; Fisch et al., 2021; Momtaz, 2018). Other studies use trading volumes on the exchanges to assess investor participation in ICOs as a proxy of the likelihood of longer-term success (e.g Florysiak and Schandlbauer (2019); Sockin and Xiong, 2018). Howell et al., (2019) include a dummy whether the ICO was listed on a crypto exchange. Using both proxies, assets raised and historic performance, Fisch and Momtaz (2020) borrow from Ritter's IPO research methodology (Ritter, 1991) and with this examine the price series and the trading volume six months after exchange listing.

This study's main approach emphasizes the fundamental view of an ICO organisation and its success in innovation. Instead of the trading volume, this study is based on the presumption that relative return and volatility contain sufficient information on determining asset value from the price timeseries. my sample comprises of ICO organisations that are listed on the exchanges and are tradable. I purport that my modified IR measure is a functional proxy for long-term performance, as it is based on the premise that successful ICO organisations exceed the technology benchmark set. my study proposes a novel metric for measuring the network effects of ICO organisations. This is achieved through a price series analysis using the modified information ratio (hereafter IR) that benchmarks the technology or utility based on the relative value signalling information that the public market offers. This study is motivated by the need to find an alternative approach to the short-term method that may be based on investor sentiment rather than on fundamental based market information. Hence, I attempt a foundational approach to ICO organisational success, more closely linked to fundamentals. Moreover, I examine the cointegration between ICOs and the main cryptocurrencies to assess the market standing of ICO organisations through ICOs innovation rollout after they are listed on an exchange. These metrics may be conducive to provide for a more accurate valuation of ICO organisations.

The data is collected from the databases with a set criterion for data sourcing. The performance comparable market benchmark technology is ethereum, and it is utilized to measure organisations relative performances. Bitcoin was also assessed for this as well, but the ethereum was tested to be a closer, relative benchmark for the ICOs. One of the main assumptions in this study when assessing the ICO price series is that, in the long-run, the asset prices follow fundamentals. The empirical analysis in this study shows and measures that network effects contribute to the value of an ICO organisation. This can be revealed in their relative pricing. If the ICO organisation is not mature and the investor base would not find ways to contribute to its fundamentals as users by not be able to support the network effect, nevertheless, the investors may show price speculation by contributing to the investor feedback loop (Shiller, 2003). Whilst these ICOs may be susceptible to sentiment investing and speculation, these organisations are innovative. Noting this promising value, the recommendation of this study is to support the best practise foundation for these digital entities. This prompts the necessity for forming a policy to regulate for investor and user protection. The findings of this study are multitudinous but also point to the need for further study on network effects in ICOs. The results can also be useful for managing resources in ICOs, blockchain organisation or generally digital value-creating organisations. Also investing strategies in similar digital instruments can be formed with using modified information ratio. The study's long-term research focus bases on the institutions preference to invest on the long-term.

The remainder of this study is organised as follows. *Section 2* reviews the relevant literature and outlines the empirical predictions. *Section 3* presents the data, summary statistics and the empirical strategy. Then, *Section 4* presents the estimates for the variable effects and *Section 5* concludes.

5.2 Background and research questions

Scholarly inquiry into ICO organisations is a recent development. ICOs are issued on digital platforms for fundraising for innovative ventures. Noting that ICOs may engage a new investor base among retail investors, one can infer there is great potential for dynamism from the perspective of *disruptive innovation*, which at its core purports the importance of the product/service demand growth among customers that are less than institutional type (Christensen et al., 2015). Start-ups are better at innovation compared to incumbent established businesses due to their ability to focus on innovation that is apart from production and marketing (Holmström, 1989). Intuitively, this contributes to the applicability of the IR to measure the innovation against the existing market technology due to single product focus of a typical ICO organisation. The possible upend of technological innovation is raising capital in a dynamic and improved manner that is especially based on crowdfunding and enhancing liquidity among participants in the economy. These comprise a large investor base, with smaller investment proportionalities. This can contribute to the higher inclusion of investors that might not invest through the traditional platforms. This methodology also offers instant pricing and possible liquidity. Also, there seems to be a real market need for a new source of funding for these digital based organisations. Whilst the share of intangible assets in companies' value are estimated to be in figure around 80%, the start-up or SME organisations without tangible assets face difficulty in raising assets from the traditional lending sources (Ogier, 2016).

The literature stresses that investment in crypto assets entails several agency problems. For instance, Blaseg (2018) points out that the ICO market entails high information asymmetry, which stems from the reliance on voluntary disclosures that is enforced by the unaudited investor communication and varied project quality. In the previous literature, asymmetry of information is observed when agents can benefit from withholding information where there is no requirement for external transparency (Dang, 2017). Chod and Lyandres (2019) relate Akerlof's theory (1970) *market for lemons* to describe the ICO marketplace for its unregulated nature. Nevertheless, through listing at an exchange, the ICOs have improved their price discovery and their channels for distributing information on the quality of the project to the investors. This, however, might disappoint investors losing their invested capital.

Conversely, ICOs higher transparency through disclosures, is positively connected with the ICO success (Howell et al., 2019), as well as the ICO listing onto an exchange. In addition, Momtaz (2020) discussed the issue with ICO CEO incentives and project loyalty which may be at odds with the motivations and incentives of the investors. Similarly, conflicts of interest for motivations between entrepreneurs and investors related to the timing and the volume of distributed tokens are reported by Chod and Lyandres (2019).

5.2.1 Network effects in ICOs and technology facilitation

The value creation opportunity for the ICO organisations is attractive as the digital asset market is still in its infancy and is looking for its best technology solutions and practises. For instance, drawing from the network effect framework in information technology (e.g. Weitzel et al., 2000), one can infer that, while bitcoin may be the most dominant of cryptocurrencies and digital assets, it is not dominating. By the end of 2019, no single cryptocurrency was holding a position of dominance at a near 90% level of market capitalisation. This high percentage is intuitive and lends itself from USD dollar trading volumes against other currencies or Google search engine usage that both stand at comparably similar market dominance at a near 90% level at end of 2019. For these examples, the network externalities approach suggests that there is market dominance. The lower dominance levels show a heightened probability of the market tipping to favour the competitor as a large part of the market are not utilising the largest market share holder's network system. Bitcoin's market capitalisation was estimated to be at 51.61% by Coinmarketcap[58] of all crypto assets end of 2019. It is not unlikely that bitcoin may be surpassed by other technology in the future, due to its pre-coded scalability limitations that make transactions on its blockchain more expensive when it appreciates in value, and the high latency of cleared transactions.

According to Peterson (2019) the virus-like exponential growth in bitcoin's price can be explained by Metcalfe's law (Gilder, 1993). This law is a heuristic notion that proposes that the value of a network is measured as proportional to the squared number of users, or N^2 (e.g. Hendler and Golbeck, 2007). The higher participation figures in bitcoin are not sustained in the long-term, as new owners have been motivated to trade it rather than utilise the blockchain

[58] Link: www.coinmarketcap.com

further for real transactions in the formal economy. Metcalfe's Law calls for naïvely applying the network's valuation by treating the users equal in their participation. Whilst the growth in the network's value might not be linear, the N^2 equation of bitcoin's user number growth might not be the best descriptive model for price development (Briscoe et al., 2006). However, this rule points to the growth in value when users are added and bring along their added network externalities (e.g. Hendler and Golbeck, 2007). The value estimations would need better modelling. Dolfsma and Ende (2004) proposed the price-performance ratio as a measure to assess network effects in computing and information technology. Also, Belleflamme and Peitz (2016) propose that the peer-to-peer systems' relative quality of the users' interaction, e.g. they may contain higher quality information or assurance, also adds value to the network. Here the approach is relatively similar to capturing relative price-performance to understand the relative quality.

The challenge of ICO valuation is that whilst the ICO token may be traded on an exchange, the product/service itself may not be fully developed. Consequently, then the ICOs long-term value then would be reliant on perceived future demand-pull whilst preceding the technology-push. In addition, there are regulatory or economic structure issues that may hinder the demand even for the newly created and existing innovation. The ICOs are usually not registered legal entities such and this unregulated nature brings uncertainty in upholding economic agreements among parties and that the regions have established financial services. Heterogeneous situations would be typically expected from this environment in which emergent technology-push and demand-pull factors interact (Hyundo, 2018). In addition, as in traditional financial markets, the ICO marketplace is characterised by the presence of heterogeneous investors (Fahlenbrach and Frattaroli, 2019) but also heterogeneous users (Katz and Shapiro, 1994; Bakos and Halaburda, 2019). Some investors have shorter investment horizons and present-biased preferences and the users' preferences can hinder good's wider adaptation by limiting the network size or sustaining the existence of multiple simultaneous networks. In the latter case, if the market is undecided, and the dominating network system is more susceptible for tipping points.

Network effects are driven by the technology's ability to scale up its user base. Rather than consumer consuming a service, e.g. human-provided unit of single-use customer service, the digitally created service may be scalable among users and the duplication can be unhindered. This would suggest that these digitalised services are cheap to produce on the long term on low margins. Consequently, ICO tokens have a user and investor agency balancing dynamics, as the scalability with the cost of utility interaction seeks equilibrium for pareto optimal price. This relates to the exclusion principle on unique ownership and cost of duplication or usage. In other words, as the real returns of these digital services can be low, like in facilitating transactions, they must be high volume to attract investors. This is when the value added by user network externalities come into play. Whilst there might be a low entry point to provide these technology solutions, the network sizes and relayed externalities will matter. Therefore, whilst the technology enables, it is the demand, and specifically, in this case, the demand-side economies of scale feature that adds the value for ICOs. Bitcoin might be different from this, as to function in scale, it will require complementary services. For example, as a service that offers a payment transfer pool where the payments remain within the bitcoin pool and do not transfer on the blockchain.

Katz and Shapiro (1986) investigated the necessity of compatibility of utilities for the most superior technology. Bitcoin has relatively few extant complementaries offered compared to the USD dollar that is utilised for transacting and benchmarking many global financial instruments from e.g. mortgage rates to commodity futures pricing. The network effects of competition between complementary offerings, where participants make differentiation, was investigated by Economides and Salop (1992). They suggest that integration and compatibility are driving factors in markets as they provide more utility to users, as explained earlier with the usage of US dollars. Whilst bitcoin may serve more as a store of value, even if it was primarily designed to facilitate transactions (Nakamoto, 2008), the ethereum platform offers participants the facility for further complementary goods. In the majority of the cases, the ethereum was utilised as a platform to raise funds for the ICOs. This does not say that the ICO projects themselves would be bound to use that platform or that their offering was ready for deployment when it was created on that platform (Fahlenbrach and Frattaroli, 2019), but the tokens were offered through ethereum. These ICO tokens may have been on sale for ether, but also other currencies or fiat currencies may have been accepted.

In the literature of Initial Public Offerings (hereafter IPOs), apart from IPO characteristics, trading volume is said to be positively related to the investor sentiment, as well as, their first day returns. (Baker and Wurgler, 2007). Dorn (2009) finds evidence on Internet companies' IPOs performing comparably worse in secondary markets and purports that retail investors, guided by sentiment, push the prices above the fundamental value. Another significant factor for IPO performance is the role of the underwriter quality. Barber and Odean (2008) and Eckbo and Norli (2005) document that higher rankings of underwriters have a positive effect on IPO returns in secondary markets. There is no exact counterparty that resembles an IPO underwriter in the ICO market. The closest notion to a traditional underwriter may be the cryptocurrency exchanges that offer Initial Exchange Offers (IEOs).

ICOs, that as start-ups or SMEs, are exceedingly more premature compared to traditional organisations in the IPO stage which usually have established cash flows which are then accounted for when valuing an IPO. This is the result of the greater regulation of IPO's and their related incorporations and traditional discounted cashflow valuation. Further, the traditional investment base of an IPO involves stages of earlier investment rounds from friends and family; angel investors; venture capital; private equity. After this, the market will work as the mechanism for the stock valuation. Li and Mann (2018) propose that when the 'good' is available for use, the 'wisdom of the crowd' will assess its quality and signal its economic value. These dynamics differ for ICOs. Whilst the marketing team members at ICOs contribute to the asset raising in a form of sponsoring the participation in the ICO token investing, the early stages or non-existence of the marketable good itself may be a less than optimal use of ICO organisational resources. For simplicity, the organisational manager is presumed to be restricted in allocating resources between the fund-raising/marketing and then the proposal delivery. The approach to enhance the network effects of the product by reaching out to expand the investor base is sound, but this investor base may seek to take trading profits instead of buy-and-hold. When comparing back in time the recent ICO launches to the dot-com IPO frenzy, Demers and Lewellen (2001) make the point that IPO marketing can translate for the increasing user numbers for internet companies. As follows, the pre-product ICO fundraising may thus be an underutilised opportunity and present to be less than optimal organisational growth strategy.

5.2.2 Research hypotheses

The hypothesis can be formed that assets raised on an own ICO organisation's own propriety blockchain, instead of platforms, such as ethereum, has a positive impact on the long-term performance of that ICO organisation. The ICOs helps to gain not only investors but also users ICOs, which in effect can be presumed to described by as network effects. This can be formulated be tested empirically with using the IR measure as follows:

Hypothesis 1 (Null): Asset raising on ICOs' own proprietary blockchain does not have a positive impact on the long-run success of the organisation.

Hypothesis 1 (Counterfactual): Asset raising on ICOs' own proprietary blockchain has a positive impact on the long-run success of the organisation.

To help to make predictions for the long-term success of ICO organisations utilising the price timeseries, a presumption can be made that they can benchmarked to the extant technological innovation in the marketplace. Cointegration analysis of ICO price performance to ether can be employed to aid in that process. The cointegration will estimate the assets long-term equilibrium relationships to each other's using only the price timeseries. Moreover, Momtaz (2020b) proposes the ethereum network closeness can convey systemic risk for ICO tokens and thus introduce centralisation. The ICO organisation's own innovation can be seen as their idiosyncratic characteristics, and these show through as different price movement to the market beta or benchmark. The economic equilibrium theories support the cointegration of asset prices to the same fundamentals in the long-term (Hamilton, 1994; Johansen, 1998). While cointegration analysis has been previously employed to the ICO market index with the major cryptocurrencies (Masiak, 2019), this has not been inspected on the level of a single ICO organisation. Here cointegration relationship to the employed technology fundamental is estimated and the following hypothesis is proposed:

Hypothesis 2 (Null): Cointegration to ethereum does not have a negative relationship with market adjusted long-run returns of an ICO organisation.

Hypothesis 2 (Counterfactual): Cointegration to ethereum has a negative relationship with market adjusted long-run returns of an ICO organisation.

The ICO organisations use the internet to market their offerings through various platforms and this effect is presumed to be noticeable for the asset raise. However, inspecting the ICO teams' LinkedIn networks can help to estimate the possible marketing contribution opportunity cost from development to the ICO long-term performance. Here below is the associated null hypothesis and, for the benefit of clarity, the alternative hypothesis:

Hypothesis 3 (Null): The number of LinkedIn connections by the ICO team members does not have negative relationship with the market adjusted long-run returns.

Hypothesis 3 (Counterfactual): The number of LinkedIn connections by the ICO team members have negative relationship with the market adjusted long-run returns.

Similarly, with the team's LinkedIn connectivity, there is also the issue with later abandoned LinkedIn profiles that had been available during the asset raise. These can also be inspected for the asset raise and auxiliary inspected how these contribute to the ICO's long term performance. The below hypothesis is thus formulised:

Hypothesis 4 (Null): The number of abandoned LinkedIn profiles by the ICO team members does not have a positive relationship with the market adjusted long-run returns.

Hypothesis 4 (Counterfactual): The number of abandoned LinkedIn profiles by the ICO team members has a positive relationship with the market adjusted long-run returns.

5.3. Data and methodology

To analyse ICO organisations' network effects, 3 datasets are utilised: ICO descriptive data, ICO organisation price timeseries and ICO organisation LinkedIn profile data. The multivariate regressions models including fixed country effects utilise the clustering by time for possible samples' variable heteroscedasticity. Multiple model variations are used for showing the consistency in coefficient results. This is to mitigate biases emitting from missing variables.

5.3.1 ICO data and summary statistics

The ICO descriptive sample consists of 675 ICOs which are drawn from the ICObench online database[59] at the end of 2019. These data are shown in Table 5.1. The data is self-reported by the ICO organisations through a form submission and the ICOs information entry is supervised by the database maintenance[60]. This sample only includes ICO's that have registered onto the ICObench and whose daily time-series can be sourced through Kaiko Digital Assets[61], which is a crypto asset data provider. Fisch and Momtaz (2020), utilise ICObench online information on the ICO organisations, and use Big Data technologies. The data from the ICObench for the analysis is challenging due to missing reported data. This was noted during the data pre-analysis that also included the regressions model specifications which lost power or showed lower informativeness by utilising only constructed dummy variables. This study's data capture included an additional year after Fisch and Momtaz (2020) study sample.

The ICObench provides a utility or payment token classifications for the sample. There were 21 payment and 654 utility tokens reported in the 675 observation sample. This data was used in pre-liminary regressions but showed no significant results. Howell et al. (2020) present a 12-category breakdown for the ICO industries and find that advertisement, new blockchain protocol and real asset tokenisation have the largest significant effects to exchange listing success, and generally find that decentralised, consumer focused two-sided platforms or marketplaces are the largest business model categorisations for the ICO issuers.

[59] Link: www.ICOBench.com

[60] The ICO registration application on ICObench is broadly the following: "Team must consist of at least 3 members with real names. White paper must be not less than 12 pages. The application must have active social links. Website must be active and do not cause suspicion."

[61] Link: www.kaiko.com

Table 5.1

ICO descriptive summary. This table summarises the data from ICObench, self-reported ICO descriptive data, Kaiko Digital Assets price timeseries, team member and advisor data from LinkedIn is as reported on the ICObench. The data is as of 31.12.2019. The IR is calculated as the excess return of the ICO over ethereum with the excess volatility over Ethereum. The IR is winsorized between-1 and 1. The sample's employee team size is truncated to 30 whilst the advisor number by an ICO is truncated to 10.

	N	Mean	Standard Deviation	Median	Minimum	Maximum
Total Sample of ICO	675	–	–	–	–	–
Dummy - Separate Blockchain dummy	675	3.70%	0.19	–	–	–
Dummy - Ethereum cointegration dummy	675	14.37%	0.36	–	–	–
Raised 1m USD	469	29,070,646	201,321,460	10,220,400	19,121	4,197,956,135
Distributed in ICO	403	50%	21%	50%	2%	100%
Number of tokens for sale	433	35,448,395,217	670,623,877,318	201,000,000	210,000	13,950,760,545,239
Number of currencies accepted	537	1.81	1.3	1	1	9
Last day of ICO	556	24/01/2018	199.7	29/12/2017	21/08/2015	04/12/2019
Quarter	556	10.75	2.2	11	1	18
Trading days	675	536	270	568	11	1799
Token price in USD	580	204	2996	0.14	0.0001	60000
IR - winsorized - against Ethereum	675	-0.46	0.47	0	-1	1
IR - winsorized - against Bitcoin	675	-0.64	0.42	-1	-1	1
IR against Ethereum	675	-0.63	0.90	0	-13	2.1
IR against Bitcoin	675	-0.93	0.96	-1	-13	2.0
Number Team member total	622	10.20	6.2	9	1	30
# Team members – male	622	8.59	5.1	8	1	28
# Team members – female	415	1.61	1.9	1	0	12
# of Linkedin profiles by team	476	7.97	4.9	7	1	26
# of Linkedin contacts by team	508	13,441	23,103	6,436	12	332,074
# Advisor	403	5.63	2.8	6	0	10
# Advisor -male	405	5.35	2.7	5	0	10
# Advisor -female	128	0.39	0.7	0	0	5
# Team members + Advisors	626	13.78	7.3	13	1	40
Dummy - a female team member reported	675	61.15%	0.49	–	–	–
Dummy - an Advisor - female reported	675	18.96%	0.39	–	–	–
Dummy - an Advisor reported	675	59.85%	0.49	–	–	–

Table 5.2 compares the ICO asset raising platforms. Ethereum was reported to be utilised as a platform on 595 observations or 88% of the share. The separate blockchain or also as referred to the ICOs proprietary blockchain had 25 occurrences. That category will be used in structuring the hypothesis on network effects. ICOs' also used Waves on 10 occurrences and NEO in 8 cases. These data were also collected from the ICObench database. There were no occasions of missing data respective to this variable.

Table 5.2

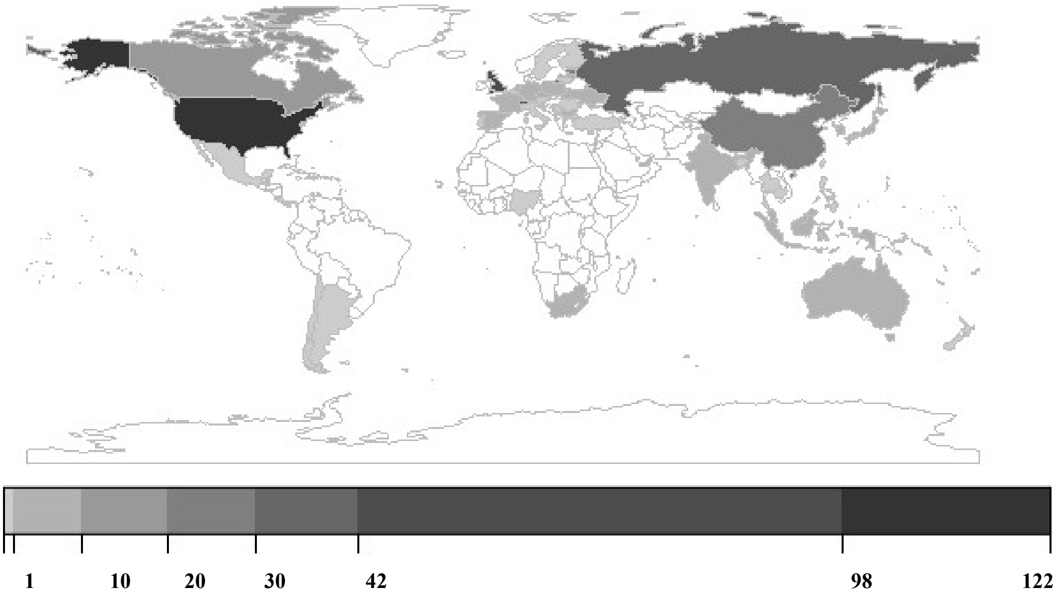
Platforms utilised for the ICOs. The ICO platform data is as reported on the ICObench database. The percentages are calculated from the sample of 675 ICOs.

	N	%		N	%		N	%
Bitcoin	4	0.6%	NEM	4	0.6%	Separate blockchain	25	3.70%
Bitcoin Gold	1	0.15%	NEO	8	1.2%	SpectroCoin	1	0.15%
BitShares	3	0.45%	NEP	1	0.15%	Stellar	3	0.45%
Counterparty	1	0.15%	Nxt	1	0.15%	Stratis	1	0.15%
EOS	2	0.30%	Omni	2	0.30%	Ubiq	1	0.15%
Ethereum	595	88.15%	QRC	2	0.30%	Waves	10	1.50%
ICON	1	0.15%	QTUM	1	0.15%	Zilliqa	1	0.15%
Infinity Blockchain	1	0.15%	Ripple	1	0.15%			
Komodo	2	0.30%	Scrypt	3	0.44%			

Table 5.3 provides a breakdown of ICO country domiciles. For instance, the USA was reported to be the domicile with the highest amount of ICO organisations at 122 observations. It was followed by Singapore with 98, and the UK with 44 reported ICOs. What is notable is that these countries hold both technology and financial hubs. There are country domicile regroupings to the regional level when there are less than three reported observations by country. This is to avoid interpreting intrinsic ICO project qualities as location fixed effects.

Table 5.3

The ICO domicile data is as reported on the ICObench database as end of 2019. The percentages are calculated from the sample of 675 ICOs. Other Africa include two Mauritius and one Nigeria ICO observations. Other America include the following ICO observations: two Argentina, two Costa Rica, two Saint Kitts and Nevis, one the Bahamas, one Chile, one Mexico and one Panama. Other Asia include the following: one Bangladesh, two Cambodia, two the Philippines, two Taiwan, one Thailand and one Turkey. Other EU include: two Austria, one Belgium, two Cyprus, two Finland, two Italy, one Luxembourg, one Portugal, one Romania and one Sweden. The Other Europe include the following ICOs: one Armenia, two Lichtenstein, one San Marino and one Serbia.



	N	%		N	%
Belize	5	0.7%	Oceania	12	1.8%
British Virgin Islands	6	0.9%	Poland	4	0.6%
Bulgaria	4	0.6%	Russia	36	5.3%
Canada	18	2.7%	Seychelles	4	0.6%
Cayman Islands	15	2.2%	Singapore	98	14.5%
China	24	3.6%	Slovenia	10	1.5%
Czech Republic	3	0.4%	South Africa	3	0.4%
Estonia	21	3.1%	South Korea	8	1.2%
France	6	0.9%	Spain	4	0.6%
Germany	9	1.3%	Switzerland	42	6.2%
Gibraltar	15	2.2%	UK	44	6.5%
Hong Kong	20	3.0%	Ukraine	3	0.4%
India	6	0.9%	United Arab Emirates	5	0.7%
Indonesia	4	0.6%	USA	122	18.1%
Israel	8	1.2%	Other Africa	6	0.9%
Japan	9	1.3%	Other America	10	1.5%
Latvia	5	0.7%	Other Asia	9	1.3%
Lithuania	7	1.0%	Other EU	13	1.9%
Malaysia	4	0.6%	Other Europe	5	0.7%
Malta	7	1.0%	NA	36	5.3%
Netherlands	8	1.2%			

5.3.2 ICO organisation price time-series

Kaiko Digital Asset sourced ICO organisation price timeseries from various crypto exchanges were used to calculate the Information Ratio (IR) on daily close prices at UTC midnight[62]. The analysis utilises IR due to its applicability to measure market relativeness while utilising the marketplace's price signalling on the ICO organisation quality. The IR is calculated as the excess return of the ICO token R_i over ether R_{ETH}, in proportion of compared excess volatility σ_{iETH}. To formulate the equation:

$$IR_i = \frac{E(R_i - R_{ETH})}{\sigma_{iETH}} \quad (1)$$

The presumption is made that ICO organisations with a single business aim are seeking to create a value-added innovation over the base market platform technology, such as ethereum, and thus it may be compared to this benchmark. This is a novel approach to assessing the quality solely on the price series. Other existing approaches may mix these with ICO market capitalisation, the number of users or by trade volume. With the IR approach, the intuition is to capture the long-term fundamental value of these projects, and possible utility and mitigate the inputs from short term sentiment trading. Owning to the existence of the ICO organisations marketing efforts after the ICO and absence of securities market regiments governing investor relations, the cause of investor sentiment may not be considered exogenous as in the stock market (e.g. Baker and Wurgler, 2007). The research into the success of the ICO organisation in the long-term, and this might imply a technological innovation value in the form of network effects and cointegration. The IR may be used to assess investments by their consistency of surpassing the market and this makes it more applicable to market relative comparison than Sharpe Ratio (Sharpe, 1994). In addition, Sharpe Ratio relates to the market to risk-free rate as well as the to the differing volatility. Here it is assumed a benchmark measure to compare an ICO to already functioning technology such as ethereum.

ICO tokens are tradable 7-days a week and 24-hours a day. The timeseries is selected by its earliest exchange listing to any quoted currencies. These may be quoted in bitcoin, ether, tether, BNB, quantum, OKB, dogecoin, US dollars, CKUSD, EOS, HT, Chinese renminbi, Australian dollar or South Korean won and the series are then

[62] For the information completeness, CoinMarketCap and Coingecko were also utilised as auxiliary data source.

converted into the USD. The mean history of the sample's trading days is 534 days and were calculated until the year-end of 2019.

This analysis applies ethereum as the primary market performance benchmark, as the sample's ICO tokens daily returns show higher correlation of 0.293 and have 100 assets cointegrated with it. The cointegration test specifications are presented in appendix 3. The comparable for bitcoin are 0.26 and 86. Moreover, 88.2% (595) of the sample's 675 ICOs have utilised ethereum as their funding and possibly operational platform. Four ICO organisations utilised bitcoin for asset raise, which represented less than 0.6% of the sample.

The sample's median price is 0.14 USD. The mean of annualised volatility of the ICO sample is 362%. This is very high even when it is compared to the annualised volatilities of ether at 134% since its launch in August 2015 or bitcoin's 77% during the same period. The mean annualised return of the ICOs across the time periods is -248%, with a median annualised return of -185%. The ICOs' IRs are winsorized between a range of -1 and 1 to deal with the outliers. Moreover, heuristically in investing, IR of -1 indicates a very poor performance whereas IR of 1 shows a great performance. The winsorized IRs to ethererum have a mean of -0.47 with a standard deviation of 0.5. The equivalent figures for the bitcoin winsorized IRs are -0.62 with 0.5.

5.3.3 ICO organisation LinkedIn profile data

A secondary investigation is also made into the composition of the human capital and networks within the ICO industry. The human capital information was extracted from the ICObench database using a web crawler technology. Based on the reported team information in the ICObench database, the dataset has 8,672 ICO organisation members of both team members and external advisors. The male employees represent 81.3% of the sample (i.e. 5,346 individuals) with the figure for 18.7% female employees (i.e. 1,001 individuals). The ICObench database also lists project advisors. The sample consists of 2,325 advisors of which only 6.8% are female. The online Gender-API[63] was utilised as the gender definition tool in this study. The gender suggestion was made with the input date of name and country when this data was available.

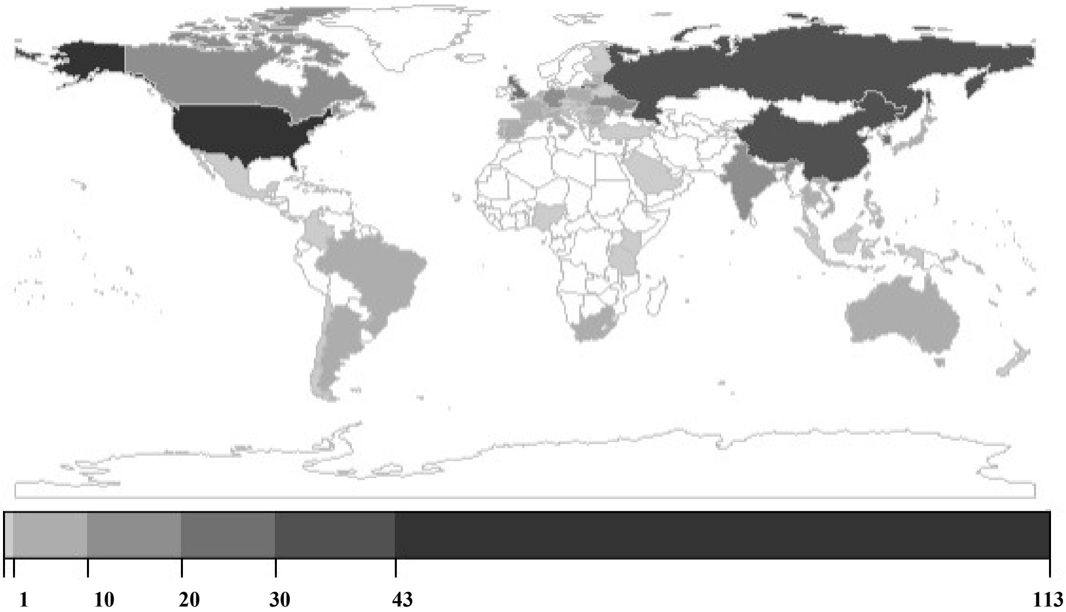
[63] www.gender-api.com

The LinkedIn profiles were the most reported social media platform in the ICObench database. Another web crawler was utilised to search for the title, location, number of connections as well as a number of followers through the direct profile links provided on the ICObench. On average, the sample's male team members are estimated to have 1,822 connections (N: 4,328), whilst the females have 1,350 (N:692). Other social media listed were Twitter, Facebook as well as GitHub. The presumption is made that these reported LinkedIn profiles are not time-varying on ICObench due to the sample's 385 reported no-more existing LinkedIn profiles at end of 2019. LinkedIn profiles are generally assumed to help in branding personal career profiles rather than only for an opportunity/job duration. The sample's 65.9% share of the male advisors had reported a LinkedIn profile in the ICO database. They had an average of 19,559 LinkedIn contacts. The equivalent figures for female advisers are 87.4% with an average of 3,586 LinkedIn connections. Due to the data limitations[64], which is expected to affect the groups equally, the number of connections is a downward estimation. Table 5.4 presents the ICO organisations' reported team member's highest frequency cluster by country or region as reported on LinkedIn profiles sampled from ICObench. The USA, Russia and China were the most usual locations for ICO organisations' team member clusters. There are regional regroupings for the LinkedIn country locations when there are less than three ICO observations by country.

[64] As by a default profile setting, LinkedIn may only show "500+ connections" rather than the exact figure.

Table 5.4

LinkedIn team locations. The highest number team member location by country data is gathered from the reported LinkedIn profiles in the ICObench database. The percentages are calculated from the sample of 675 ICOs. African locations include ICOs: one Kenya, one Nigeria and one Tanzania. Oceania includes: eight Australia and one New Zealand. Other Americas include one Chile, one Columbia and two Mexican ICOs. Other EU include two Austria, one Belgium, two Cyprus, one Czech Republic, two Finland, one Hungary and two Malta. The Other Europe include an ICO from Armenia, Belarus, Liechtenstein, Monaco and Serbia.



	N	%		N	%
Africa	8	1.2%	Russia	43	6.4%
Brazil	3	0.4%	Singapore	16	2.4%
Bulgaria	7	1.0%	Slovak Republic	3	0.4%
Canada	18	2.7%	Slovenia	10	1.5%
China	33	4.9%	South Korea	24	3.6%
Estonia	5	0.7%	Spain	5	0.7%
France	7	1.0%	Switzerland	10	1.5%
Germany	11	1.6%	Taiwan	3	0.4%
Hong Kong	7	1.0%	Thailand	4	0.6%
India	13	1.9%	UK	29	4.3%
Israel	11	1.6%	Ukraine	13	1.9%
Italy	6	0.9%	USA	113	16.7%
Japan	6	0.9%	Vietnam	4	0.6%
Latvia	3	0.4%	Oceania	9	1.3%
Lithuania	15	2.2%	Other Americas	7	1.0%
Netherlands	3	0.4%	Other Asia	6	0.9%
Philippines	3	0.4%	Other EU	11	1.6%
Poland	3	0.4%	Other Europe	6	0.9%
Portugal	4	0.6%	NA	190	28.1%
Romania	3	0.4%			

ICO organisations are deemed to be highly human capital intensive (Campino, 2020). And this study draws on accessible online data to see if there can be made a differentiation between marketing and development roles or ICO resource allocation. The sample's female participation as team members and advisors is 13.4%. This is a very low figure across all the industries, especially when this figure encompasses all occupational roles including e.g. development and marketing and seniorities. To illustrate, the estimation of women working in technology-related roles stand at 15%[65]. In financial services, this figure is nearly at parity 50% across all the occupational roles, but majority in less senior level roles which has been an area of that is addressed (Catalyst, 2020). This lower comparable seniority is also seen in this study's ICO team sample when looking at the figure 2 and 3 in appendix 2 job role title wording between the men and women. Beside the technology skill gap, this could also be an indication that ICO organisations are perceived to be riskier organisations for careers (Claussen et al., 2016) and females are perceived to be more risk averse in general (Eckel and Grossman, 2008; Borghans et al., 2009). The figures in appendix 2 show the occupational roles present at ICOs: male (Figure 2). and female (Figure 3.) titles including the advisors. For men, the highest frequency titles relate to the words of 'developer', 'co-founder' and 'CEO', whereas for women, the 'manager', 'marketing' and 'head' are more prevalent. The female titles resonate less senior as well as pointing toward involving business development tasks rather than product development. When crudely comparing the developer word frequency in job titles, 5% of women team members included this whilst the equivalent was 11% for men. This represented men's highest frequency word in the job title, whilst this was the 6th for women.

The ICO organisations are by majority small-sized teams. Out of 675 of the observed ICOs, only 12 of them have more than 30 employees. This corroborates with previous findings (OECD, 2019b; Howell et al., 2020), which describe these organisations as micro-SMEs. The sample only includes 30 first reported employees and 10 first reported advisors. The sample's reported mean team size is 10 members. The equivalent mean advisor number is six by an ICO organisation.

[65] PWC, Women in Tech: Time to close the gender gap, 2017.

5.3.4 Empirical strategy

I estimate Tobit models (Tobin, 1958) of ICO long-term success relative to the market by employing the IR measure constraining the scores between -1 and 1. The base model, in which the restricted IR of the ICOs is the dependent variable, is estimated in the following form:

$$IR_i \;= \beta_i + \beta_1 R_i + \beta_2\, O_i + \beta_3 (R_i \times O_i) + \beta_1 D_i + \varepsilon_i, \tag{2}$$

where: $\mathrm{IR} \epsilon [0,1]$, representing market adjusted performance to ethereum. R denotes the amount of assets raised in USD millions. O denotes the foundation upon own proprietary blockchain and ε_i is the error term. The interaction between assets raised (R) and own, proprietary blockchain (O) is used as a proxy to measure the network effects. D represents the further individual characteristics of the ICO. ε_i is the usual error term.

To establish robustness, an alternative variable to assets raised is used, which also caters to explanatory power lost by missing values.

Hence, my second specification used the number of tokens (T), the price of a token (P), own proprietary blockchain (O) and the following interaction terms:

$$\begin{aligned} IR_i \;&= \beta_i + \beta_1 T_i + \beta_2 P_i + \beta_3 O_i + \beta_4 (T_i \times P_i) + \beta_5 (P_i \times O_i) \\ &+ \beta_6 (T_i \times O_i) + \beta_7 (\mathrm{T} \times P_i \times O_i) + \beta_1 D_i + \varepsilon_i \end{aligned} \tag{3}$$

In my third specification, I incorporate the cointegration between the ICO organisation and the price of ethereum, in the form of a dummy variable CI_i^{eth} which take values 0 or 1. The steps for the cointegration can be viewed in appendix 2.

$$IR_i \;= \beta_i + \beta_1 R_i + \beta_2\, O_i + \beta_3 (R_i \times O_i) + CI_i^{et} + \beta_1 D_i + \varepsilon_i\,, \tag{4}$$

The final estimation describes the explanatory factors for the ICO's asset raising success that is defined as the logarithm raised in USD millions using the ordinary least squared model (OLS). This estimation is auxiliary in the investigation of the organisations long-term success from the outset of this ICO sample, as this is not a representative sample of all ICOs, but only this study's sample and which are registered onto an exchange. This sample may show survivorship bias in the ICO universe and make the performance of the assets better. Nevertheless, it helps to understand the sample and helps to calibrate the IR method used in the long-term performance analysis. The final model is simply formulated as:

$$Log(M_i\ ) = \beta_i + \beta_1 D_i + \varepsilon_i \tag{5}$$

The regressors in *D* represent variables such as dummy variables of team, advisor, LinkedIn and domicile reporting on ICObench; number of LinkedIn contacts (log), abandoned LinkedIn profiles, (log) tokens for sale and (log), price in USD, and ICO end date by quarter. The proprietary blockchain dummy variable was also regressed with the dependent variable during pre-analysis, but this did not provide any significant results. For the result robustness, there are eight specifications, including two specifications with fixed effects on country team location, as gleaned from LinkedIn, and reported domicile as shown in the ICObench database, to assess the variables effects which may again have different sub-sampling due to missing observations.

5.4 Results

Table 5.5 and 5.6 present the Tobit regression estimates of ICOs computed IRs against ethereum. This is winsorized between -1 and 1. This score sums up to 2 and thus it will give the coefficients estimates the percentage magnitude that is divided by 2. Columns 1, 2, 6, 7, 8 and 9 of Table 5.5 present specifications with a single control variable, as a starting point of the analysis. Table 5.6 present the results similarly to Table 5.5, but includes control variables specification. Table 5.7 shows the regression results for the asserts raised and variable relationships. These results are discussed thematically below.

5.4.1 ICO Technology and Network effects

The network effects can be seen in pricing of the exchange listed and trading ICO when proprietary blockchain is already functioning. The base model in columns 3 table 5.5 present the interaction result of the IR for whether the assets were raised on to the proprietary blockchain by the ICO. Whilst the 100m USD raised shows 1% positive and highly significant effect on the IR score, the interaction of assets raised on a proprietary blockchain showed a 6% effect at high significance. This effect is estimated to be six times larger compared to the only assets raised coefficient. Specification 5 includes an additional cointegration variable. The results persist as they are comparably similar by sign, magnitude and significance as shown in column 3. As can be seen across all the specifications in that same table, the own blockchain variable that aggregates all the existing and own blockchain but differing technologies (or purposes) does not have any significant effect.

Table 5.5

ICO's IR against Ethereum and variable relationships

This table reports Tobit regression estimates. The dependent variable is the IR of the ICOs to ethereum. The scores are censored between -1 and 1. The standard errors are clustered by ICO end date quarters and are shown in brackets. The asterisks denote the following levels of significance: ***<0.01, **<0.05 and *<0.10.

Panel A	**(1)**	**(2)**	**(3)** *Model 2*	**(4)** Model 3	**(5)** *Model 4*	**(6)**
Raised- USD100M- (R)	0.029*** [0.01]	–	0.021*** [0.005]	–	0.020*** [0.005]	–
ETH cointegration (E)	–	--0.258*** [0.058]	–	–	-0.234*** [0.167]	-0.260*** [0.058]
ETH platform	–	–	–	–	–	-0.109 [0.082]
1bn Tokens for sale (T)	–	–	–	0.002*** [0.001]	–	–
Price of ICO token USD (P)	–	–	–	0.004** [0.0001]	–	–
Own Blockchain ICO (O)	–	–	-0.009 [0.145]	-0.182 [0.196]	-0.001 [0.143]	-0.071 [0.148]
Interaction: R*O	–	–	0.127*** [0.019]	–	0.123*** [0.019]	–
Interaction: T*P	–	–	–	-0.004*** [0.001]	–	–
Interaction: P*O	–	–	–	-0.021*** [0.005]	–	–
Interaction: T*P*O	–	–	–	0.146*** [0.036]	–	–
Log Sigma	-0.592*** [0.039]	-0.539*** [0.037]	-0.600*** [0.039]	-0.563*** [0.049]	-0.612*** [0.045]	-0.539*** [0.037]
Log-likelihood	-410.91	-615.54	-408.28	-426.81	-402.85	-614.67
Wald χ^2	5.03**	15.23***	10.39**	14.34**	21.53***	16.99***
# Observations	469	675	469	402	469	675

Panel B	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
ICO end date by quarter	-0.035*** [0.011]	–	–	–	–
Team Member	–	-0.034** [0.014]	–	–	–
Team Member male	–	0.038** [0.018]	–	–	–
10k LinkedIn contacts team	–	–	-0.278** [0.117]	–	–
Abandoned LinkedIn profile	–	–	–	-0.048** [0.023]	–
Advisory dummy	–	–	–	–	-0.001 [0.086]
Log Sigma	-0.578*** [0.036]	-0.527*** [0.039]	-0.528*** [0.044]	-0.517*** [0.035]	-0.525*** [0.037]
Log-likelihood	-489.45	-576.64	-438.21	-577.09	-623.12
Wald χ^2	9.675***	5.370*	3.950**	4.457**	0.001
# Observations	556	621	476	622	675

Further, table 5.6 presents the 100m USD raised on that proprietary blockchain interaction in columns 1, 2, 5 and 6. These specifications include cointegration indicator and location fixed effects. The coefficients in all specifications stay highly significant with large effects between 6.3% to 12%. Estimates in columns 5 and 6 are controlled with social media variables and show the higher coefficient effects at 12% for this variable interaction. This may be explained by the lost power of losing observations due to missing values, but most importantly the interaction variable of assets raised on own blockchain remains large and significant. The specifications 1 and 5 include domicile location fixed effects, whilst the specifications of 2 and 6 include the LinkedIn profile team location fixed effects. The sign, magnitude and significance stay comparably similar.

For robustness, estimate 6 in table 5.5 is included to check for any variable collinearity of own blockchain, ethereum platform-based fundraising and cointegration. To mitigate any model sample selection bias and aid the result robustness due to those missing values, also a further proxy for asset raised success was introduced. This was formulated by interacting the number of tokens sold and the token price variables. The number of tokens sold and the token price proxy relationship to the log asset raised dependent variable is explored in columns 7 and 8 in table 5.7. This proxy is similar when interacted further with the indicator variable of the proprietary blockchain. The specifications 4 in table 5.5 explores this asset raise proxy's coefficient effect. The coefficient effect magnitude is similar at 6.5% whilst being moderately significant. Columns 3 and 4 in Table 5.6 aim to replicate the prior specifications 1 and 2. These respective specifications show positive, 6.5% and 7.5% coefficient effects for the asset raise and ICO's own proprietary interaction with both being highly significant. Thereby, the null hypothesis, H1(0), of the interaction of assets raised with own proprietary blockchain having no positive impact on ICOs long-term performance can be rejected. This impact, over merely the amount of assets raised, can be explained through available user utility or as the network effect. This assessment supports the study by Uzzi (1991) that evidenced that organisations that create network effects have better chances of survival.

Table 5.6

ICOs' IR against Ethereum and variable relationships including domicile and LinkedIn team location

This table presents estimates of Tobit regressions. The dependent variable is the IR to Ethereum. The IR scores are censored between -1 and 1. The results do not display the insignificant coefficients estimated to be less than 5% of significant of team locations or ICO domiciles. The complete list country/regions can be seen in tables 3 and 4. The standard errors are clustered by ICO end date quarters and are shown in brackets. The asterisks denote the following levels of significance: ***<0.01, **<0.05 and *<0.10.

	(1)	(2)	(3)	(4)	(5)	(6)
Own Blockchain (O)	-0.054	0.023	-0.234	-0.156	-0.068	-0.090
	[0.122]	[0.116]	[0.162]	[0.156]	[0.147]	[0.146]
Raised-USD100M (R)	0.020***	0.017**	–	–	-0.086**	-0.093**
	[0.004]	[0.007]			[0.040]	[0.038]
1bn Tokens for sale (T)	–	–	0.0001***	0.0001***	–	–
			[0.0000]	[0.0000]		
Price of ICO token by USD (P)	–	–	-0.00001	0.00001	–	–
			[0.00002]	[0.00002]		
ETH cointegration (E)	-0.175***	-0.180***	-0.219***	-0.205***	-0.145***	-0.173***
	[0.048]	[0.046]	[0.053]	[0.048]	[0.056]	[0.054]
R*O	0.141***	0.126***			0.239***	0.241***
	[0.029]	[0.018]			[0.049]	[0.043]
T*O	–	–	0.001***	0.001***	–	–
			[0.0002]	[0.0002]		
P*O	–	–	-0.018***	-0.022***	–	–
			[0.006]	[0.004]		
T*P	–	–	-0.0001***	-0.0001***	–	–
			[0.00002]	[0.00002]		
T*P*O	–	–	0.125***	0.157***	–	–
			[0.039]	[0.030]		
ICO end date by quarter	-0.013	-0.008	0.001	0.0005	-0.006	-0.004
	[0.010]	[0.011]	[0.013]	[0.013]	[0.014]	[0.013]
Number of team members	–	–	–	–	-0.008	-0.012
					[0.013]	[0.013]
Team member male	–	–	–	–	0.012	0.017
					[0.016]	[0.016]
10k LinkedIn contacts by team	–	–	–	–	-0.176**	-0.137*
					[0.075]	[0.080]
Abandoned LinkedIn profile	–	–	–	–	-0.033*	-0.035*
					[0.019]	[0.020]
Country: Domicile (1, 3, 5) and LinkedIn Team (2, 4, 6)	–	–	–	–	–	–
Domicile: Africa	-0.233	–	-0.331**	–	-0.154*	–
	[0.150]		[0.147]		[0.084]	
Domicile: Bulgaria	0.252	–	0.166**	–	0.098	–
	[0.211]		[0.071]		[0.143]	
Domicile: China	0.319*	–	0.504**	–	0.142	–
	[0.193]		[0.230]		[0.312]	

Table 5.6 continued in the following page.

Table 5.6 continued in the following page.

Domicile: Japan	0.041	–	-0.142	–	-0.491***	–
	[0.230]		[0.168]		[0.090]	
Domicile: Oceania	0.149	–	0.391***	–	0.348	–
	[0.200]		[0.129]		[0.249]	
Domicile: Other Americas	0.207	–	0.447**	–	0.308	–
	[0.209]		[0.203]		[0.253]	
Domicile: Poland	-0.351**	–	-0.374***	–	-0.245	–
	[0.160]		[0.134]		[0.187]	
Domicile: Seychelles	0.381***	–	0.336**	–	0.618***	–
	[0.116]		[0.148]		[0.084]	
Domicile: South Korea	-0.436***	–	-0.421***	–	-0.416***	–
	[0.085]		[0.101]		[0.117]	
Domicile: Ukraine	0.076	–	0.513***	–	0.098	–
	[0.217]		[0.071]		[0.233]	
Domicile: United Arab Emirates	-0.140		-0.329**		0.175*	
	[0.182]		[0.160]		[0.106]	
LinkedIn team: Brazil	–	-0.090	–	0.245**	–	-0.106
		[0.288]		[0.113]		[0.302]
LinkedIn team Canada		-0.172		-0.350**		-0.216
		[0.154]		[0.143]		[0.161]
LinkedIn team: France	–	-0.301**	–	-0.325**	–	-0.270*
		[0.134]		[0.130]		[0.146]
LinkedIn team Italia	–	-0.259		-0.308**		-0.273*
		[0.163]		[0.156]		[0.162]
LinkedIn team: Japan	–	-0.644***	–	-0.513***	–	-0.666***
		[0.118]		[0.178]		[0.128]
LinkedIn team Lithuania	–	-0.347**	–	-0.310**	–	-0.355**
		[0.140]		[0.157]		[0.146]
LinkedIn team Oceania	–	0.372	–	0.431***	–	0.419
		[0.339]		[0.164]		[0.308]
LinkedIn team Other America	–	0.444***	–	0.550***	–	0.370**
		[0.156]		[0.115]		[0.150]
LinkedIn team Philippines	–	0.105	–	0.339***	–	0.120
		[0.220]		[0.118]		[0.186]
LinkedIn team Thailand	–	-0.221	–	-0.472***	–	-0.250
		[0.170]		[0.118]		[0.171]
LinkedIn team Vietnam	–	-0.464***	–	0.081	–	-0.497***
		[0.122]		[0.253]		[0.127]
LinkedIn team and Domicile: UK	REF	REF	REF	REF	REF	REF
Log(scale)	-0.832***	-0.842***	-0.821***	-0.831***	-0.825***	-0.850***
	[0.038]	[0.037]	[0.042]	[0.042]	[0.044]	[0.041]
Log-likelihood	-279.804	-275.225	-245.882	-241.840	-211.608	-202.936
Wald χ^2	61.887**	72.385***	67.452**	77.028***	51.873	72.275**
# Observations	469	469	404	404	351	351

5.4.2 The role of cointegration to ethereum

Tables 5.5 and 5.6 report highly significant and strong effects for the cointegration indicator variable. For instance, specification 2 in table 5.5 presents a negative coefficient effect for cointegration with ethereum at -12.9% on high significance. Table 5.5 columns 5 and 6 show similar results -11.7% Table 6 across all specifications show comparable effects ranging between -7.5% to -10.5%. I can thus reject the null hypothesis of the cointegration not having a negative impact on long-run ICO organisation performances. The cointegration has a strongly significant negative effect. This corroborates further Fahlenbrach and Frattaroli (2019) discovery on their application of "lottery feature" for ICOs. By this they posit that investors are attracted to the idiosyncratic volatility in investments. Own, proprietary technological innovation creates value that will have a differentiating asset base to the market. Intuitively, the ICOs with this intrinsic value feature can function as diversifying assets in a portfolio.

Beside moving jointly with the crypto market, a degree of a cointegrated relation between ethereum and an ICO token can exhibit while there may be periods of short-term pump-and-dumped ICO token price manipulation using information that do not represent fundamental or factual information of the specific ICO project and the price returns to normal. Nevertheless, the ICO timeseries will exhibit this comparable higher price volatility and no compensating return. For example, of recorded pump-and-dump activity in the ICO sample, "asset I" exhibits a cointegration at 5% statistical significance with ethereum having an unrestrained IR score of -1.14 or "asset II" with -1.28 IR score respectively. Also, ICO projects that are perceived to have weak fundamentals, e.g. no existent network effects or a weak promise of those are more susceptible to market manipulation. These ICOs are subjectable to higher volatilities with less persistent accumulative returns.

As per figure 1 in appendix 2, the 'decentralised'-word that relates to decentralized decision making, but intuitively also relating to systemic risks, is stated in excess of 30% of the ICO organisational marketing introductions. Noticeably, bitcoin was introduced during the aftermath of 2008-2009 financial crisis that a had large systematic impact on markets. Out of the 25 own blockchain sample observations, 3 ICO organisations' price series were cointegrated with ethereum. This cointegration variable is endogenous in nature and thus can be explained with other variables. However, this metric helps to indicate ICO's market standing from the price series and functions well as a control variable with providing result consistency. This is important as the sample loses power when more variables are used due to missing values or the use of only indicator variables. Further future analysis is encouraged for and with this metric.

5.4.3 Supporting ICO long-term or asset raising success factors and indicators for the IR measure.

This section attempts to place the IR measure with previous empirical findings. In conjunction it also investigates the ICO organisations' social media presence and team's time usage contribution to the project's long-term performance. Their impact on the ICO asset raise is also assessed to see the outset for the project development. This might help to form an understanding ICO organisation's resource allocation between innovation and marketing. The third hypothesis tests the empirical validity of the ICO organisation team LinkedIn 10k connections impact on the ICO's IR measure. The estimates in specification 9 in table 5.5 shows a highly significant negative effect of -8.5% for 10,000 LinkedIn connections by the ICO teams. Columns 5 and 6 in table 6 show the team's LinkedIn 10k connections coefficient effects with cointegration indicator, the timing variable and country fixed effects. Specification 5 shows with the domicile fixed effect variable -8.2% effect with a moderate effect and then specification -6.5% with lower significance with the LinkedIn gleaned team location fixed effect variable. It can thus be said with a degree of confidence that the null hypothesis of the third prediction can be rejected and the alternative can be accepted.

The fourth hypothesis also explores the role of social media in the organisation's post-ICO performance. Specification 10 in table 5.5 shows -1.9% of the abandoned LinkedIn profile by the team to the IR performance at a moderate level of confidence. Table 5.5 also shows that the effect is -1.55% at a low confidence level. Table 6 shows similar coefficient effects for specification 5 at -1.6% and for specification 6 at -1.75% both at a lower level of confidence. Whilst there is an indication of this consistently sized and negative effect, the results remain weak for not all reaching over 5% significance. The prudent approach is to consider the last hypothesis test inconclusive. These test results may support the conclusion of hypothesis 3 on social media as the test results all showed 10% significance. But most notably, the team's LinkedIn network size indicates to be a stronger explanatory variable. Both variables will be assessed in conjunction with this data samples ICO organisations' asset raise later in this section.

Whilst these variables may work as proxies for ICO's social media presence, they also are an indication of team member's time deployed that is limited resource. These variables have decreasing effect for the long-term ICO performance. The results corroborate Brown et al. (2020) findings on limited time as resource through their analysis on the time spent on social media, e.g. information sourcing versus time spent on trading.

Indirectly relating back to the human capital factors as much as the word frequency analysis of team member titles comparison allows between figure 2 and 3 in appendix 2 by gender, the gender does not seem to influence assets raised. Also, the team size does not seem to have a significant effect. Both these variable coefficient effect results are in modest contrast to the results that are evidenced earlier in in specification in table 5.5. Where the estimations show a moderately significant and negative impact for larger team but a positive impact for an increase of a male team member. When ICO organisations function with limited resources the increase in resources to product or good design delivery, or development over marketing has a positive effect on the long-term ICO project success. For the ICOs, the hiring of business development personnel on the expense of product development in the early stages of companies may be detrimental to organisational performance. Fahlenbrach and Frattoli (2019) find that many investors sell their tokens before the product is developed. ICO organisations may underutilise the opportunity by sponsoring, or marketing, immature technology with the aim to create the desired network effects. The prices would be expected to correct downward, especially if the markets lack those ICO token users. The further inspection shows that whilst these variables keep persistent signs and effects, but they are not statistically significant as shown in columns 5 and 6 in table 5.6 as the sample reduces due to missing observations. The social media derived variable are moderately significant in this regression with less observational power.

The timing of the end-date by quarter has a moderately significant negative relationship for long-term ICO price performance when inspecting estimates 7 in table 5.5. A one-year ICO ending date has a 3.8% negative effect on the IR measured performance. When the ICO launch date variable is included with other explanatory variables in all 6 columns in table 5.6, there are no demonstrably significant or large coefficient effects to the ICOs long- term performance.

Table 5.6 provides a view of the country fixed effects by domicile and by LinkedIn gleaned team location against the UK that was set as the reference country. The most consistently strong significant effects by domicile are the coefficients by Seychelles between 16.9% and 30.9% and by South Korea between -20.8% and -21.8%.

The most consistently large, significant effects by LinkedIn team location are shown by Japan at results between -25.7% and -33.3%. The other countries in America LinkedIn team indicator, which include Chile, Columbia and Mexico, display high positive effects between 22.2% to 27.8% at high to moderate significances. France, Lithuania and Vietnam show negative coefficients that also show moderate to high significances. Table 5.6 does not show coefficient effects for the locations without 5% or higher significant measure. The locational impact on asset raise effects are inspected closer in table 5.7.

The regression estimates were controlled both with location domicile and LinkedIn team location variables for robustness. The columns that use LinkedIn location variable show consistently higher explanatory power as indicated by the Wald-test measure. Most notably this can be seen in columns 5 and 6 in table 5.6. Further, according to the Wald-test results for the regression estimators. the LinkedIn gleaned location specification was more informative. This is even more striking finding when considering that the data does not have results for team grouping location on 119 cases. It is within prudence to state that the team location variable has higher informativeness than the domicile location variable, and it may be used for improved prediction of ICO long term performances. Moreover, as indicated by columns 6 and 7 in table 5.7, the team location, as gleaned from LinkedIn, can also be a better predictor of the asset raise success. Further study is encouraged in domicile, jurisdiction and team location impact. This study mainly utilises these location variables as control variables to measure and assess the significance of network effects.

When further inspecting the regressions' coefficients across all the 9 specifications explaining the log USD million assets raised in table 5.7, there are evidenced indication of the effects emitting from the project transparency, teams' online presence and professional networks. The specifications 2 and 3 findings corroborate with Howell et al. (2020) transparency's contribution to the ICO asset raising success with ICO organisations reporting data.

Table 5.7

ICO assets raised in the log millions of US dollars and variable relationships

This table presents estimates from OSL linear regressions of the logarithm of assets raised by the ICO in USD millions. The specification column 7 contains the Domicile country information and that in Column 8 incorporates the LinkedIn team information, respectively. The sults will not show less than 5% significant coefficients for countries of domicile or team location fixed effects the complete list untry/regions can be seen in table 3 and 4. For the specifications in columns 1-6, robust standard errors are d shown in brackets. For the ecifications of columns 7-8, the standard errors are clustered at the level of ICO end date quarter of years. The asterisks denote the llowing levels of significance: ***<0.01, **<0.05 and *<0.10.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Own Blockchain	0.350 [0.838]		–	–	–	–	–	–	–
LinkedIn reporting dummy	–	0.417** [0.181]							
Domicile reporting dummy	–	–	1.456** [0.608]	–	–	–	–	–	–
Team Reporting dummy	–	–	0.999*** [0.306]	–	–	–	–	–	–
Log (#LinkedIn t. contacts)	–	–	–	0.167*** [0.052]	–	–	0.154*** [0.053]	0.152** (0.064)	0.139** (0.057)
Number of team members	–	–	–	–	0.030 [0.032]	–	0.007 [0.036]	–	–
Team member male	–	–	–	–	-0.001 [0.044]	–	-0.013 [0.042]	–	–
Advisory dummy	–	–	–	–	-0.015 [0.136]	–	–	–	–
Abandoned LinkedIn profile	–	–	–	–	–	0.16*** [0.049]	0.154*** [0.049]	0.123*** [0.045]	0.094** [0.037]
Log (Tokens for sale)	–	–	–	–	–	–	–	0.232*** [0.080]	0.355*** [0.072]
Log (Price ICO USD)	–	–	–	–	–	–	–	0.189** [0.083]	0.263*** [0.080]
ICO end date by quarter	–	–	–	–	–	–	–	-0.054 [0.055]	-0.100** [0.040]
Location	–								
Domicile: Bulgaria	–	–	–	–	–	–	–	-3.132*** [0.365]	–
Domicile: Estonia	–	–	–	–	–	–	–	-1.157*** [0.375]	–
Domicile: Other EU	–	–	–	–	–	–	–	-1.453*** [0.451]	–
Domicile: Latvia		–	–	–	–	–	–	-2.179*** [0.242]	–
Domicile: Malaysia	–	–	–	–	–	–	–	-1.076*** [0.199]	–
Domicile: Malta	–	–	–	–	–	–	–	-1.283*** [0.255]	–
Domicile: Russia	–	–	–	–	–	–	–	-0.672** [0.305]	–
Domicile: Seychelles	–	–	–	–	–	–	–	-0.413** [0.197]	–
Domicile: Singapore	–	–	–	–	–	–	–	-0.588** [0.290]	–
Domicile: Ukraine	–	–	–	–	–	–	–	-1.854*** [0.214]	–
LinkedIn team: Africa	–	–	–	–	–	–	–	–	3.119*** [0.452]

Table 5.7 continued in next page

Table 5.7 continued from the previous page

LinkedIn team: Brazil	–	–	–	–	–	–	–	–	-0.821***
									[0.289]
LinkedIn team: Bulgaria	–	–	–	–	–	–	–	–	-1.452**
									[0.611]
LinkedIn team: Latvia	–	–	–	–	–	–	–	–	-3.111***
									[0.249]
LinkedIn team: Ot. America	–	–	–	–	–	–	–	–	-1.982***
									[0.240]
LinkedIn team: Philippines	–	–	–	–	–	–	–	–	-1.744***
									[0.262]
LinkedIn team: Russia	–	–	–	–	–	–	–	–	-0.656**
									[0.287]
LinkedIn team: South Korea	–	–	–	–	–	–	–	–	-0.934**
									[0.469]
LinkedIn team: Spain	–	–	–	–	–	–	–	–	1.123***
									[0.276]
LinkedIn team: Switzerland	–	–	–	–	–	–	–	–	-0.844***
									[0.290]
LinkedIn team: Ukraine	–	–	–	–	–	–	–	–	-1.023***
									[0.359]
LinkedIn team: USA	–	–	–	–	–	–	–	–	-0.587**
									[0.272]
LinkedIn team: UK		–	–	–	–	–	–	REF	REF
R^2	0.002	0.016	0.079	0.030	0.015	0.019	0.053	0.325	0.390
Adjusted R^2	0.000	0.014	0.075	0.027	0.008	0.017	0.042	0.194	0.256
# Observations	469	469	469	350	433	433	350	245	245

When analysing the results in specifications 4, 7, 8 and 9 I can see a positive impact of the higher team log LinkedIn contacts to asset raise with high to moderate significance at over 1.39% effect by a 10% increase in LinkedIn contacts. Interestingly, when the long-term success was analysed, as shown in table 5.5 and 5.6, there was a reverse negative effect induced by the log team's LinkedIn connections. This is contrary to the findings of Benedetti and Kostovetsky (2018), however, it is important to note that their inspected ICO price development period after the ICO listing on an exchange is 30 days and that their sample's averaged days to the listing of an ICO is 30.5 days. This is comparatively a short-term price performance period. The business contact networks are shown to be valuable, but they may also require resources to be maintained. Possibly by other types of human capital compared to the product/service delivery task related skills.

The number of later abandoned LinkedIn profiles by teams have a strongly significant and positive effect of 16% to the asset raise as shown in specification 3 when solely regressed against the log USD millions assets raised. These specifications were controlled with country fixed effects based on the ICO reported domicile and LinkedIn core team location. The UK was used as the reference variable.

There is no significant effect by whether the ICO organisation had reported having an advisor on ICObench. The advisory indicator variable, as reported by the ICO organisations in the ICObench database, had no significant effect on the ICOs assets raised as tested in specification 4 in table 5.7. This variable was similarly shown to be informationally redundant for the ICOs' long-term success as evidenced in the specification 11 in table 5.5. The presumption is that advisors may not be financially compensated and may be lowly incentivised for their activity and thus their contribution to the ICOs remains relatively small. The ICO organisations are human capital intensive with requiring large amounts of development and human hours.

Both 7 and 8 specifications in table 5.7 use the UK as the reference country variable. Comparing these two specifications separately, the team location variable provides higher explanatory power with higher regression goodness fit with the adjusted R^2 of 0.321 to 0.351 for the applied domicile control variable only. In this respect, the country location of the core team members variable set explains more in the asset raise than the ICO domicile. This may imply that the domicile can be arbitrarily assigned without any legal entity in the jurisdiction or connected to a possible company filing that could be offshore and remote from the team. Contrastingly, the LinkedIn team location variable may be a better indicator of teams' human capital, experience, motivations and incentives, and furthermore, the team members may be physically closer to the investor networks. The proposed latter explanation relates to a well-reported phenomenon of investor bias toward regional or familiar investment opportunities (e.g. Kilka and Weber, 2000; Feldstein and Horioka, 1980).

The domicile location effect to the log USD in millions raised on specification 7 is negative in all cases when compared to the UK. Bulgaria at -312%, Latvia at -218% and Ukraine at -185% showed to have the largest and highly significant negative effects on the asset raise in comparison to the UK. This might be due to their comparatively lower national GDP and the availability of funds to invest. Interestingly, Other EU countries that include ICOs from Austria, Belgium, Finland, Italy, Luxembourg, Portugal, Romania and Sweden, also show a highly significant negative effect at -145% by the location domicile. This could be about the investors' lack of interest in ICO projects and the existence of other available investment opportunities. Furthermore, the country comparisons were conducted naïvely, e.g. without PPP or GDP adjustments.

Of the team location, as estimated from the constructed team LinkedIn profile variables in specification 8; Africa, which contains countries such as Kenya, Nigeria and Tanzania have a highly significant 319% effect. Also, the results for Spain show a highly significant positive effect at 112% for the asset raise compared to the UK. The largest negative effects for asset raise by LinkedIn team location countries were Latvia at -308%, the Philippines at -196% and Ukraine at -104% with the highest level of significance. Interestingly, the US shows a moderately significant negative effect of -57% when compared to the UK.

Intuitively, log Token Price in USD and log Token for Sale have a significantly positive relation with raising ICO (log) assets. A 1% increase in log Token Price in USD contributes towards an increase of 37.3% in the raising ICO log assets in millions of US dollars. This is similar for log Token for Sale. The larger issuances may be anticipated to provide a more scalable market solution, for example, compared to bitcoin's pre-set limit of 21 million coins. When the bitcoin price has increased, so have the transaction fees on that blockchain. Higher token issuance numbers may also provide support for the 'lottery feature' which can attribute to the ICO performance, as here the tokens are low in absolute price at ICO (Fahlenbrach and Frattaroli, 2019). The sample's median token price is 0.14 USD with the lowest being 0.0001 USD.

5.5 Conclusion

This study examines the role of technology and network effects in the long-term performance of ICOs. The findings suggest that entailing own proprietary blockchain has a large effect on the long-term success of an ICO compared to only to the amount of assets raised. This phenomenon can be explained as the present network effect. In addition, the cointegration to the existing platform or digital currency such as ether has a large negative effect on the ICO's long-run success. Whilst the projects may have been able to raise funding, the initiatives may yet to be produced and exhibit proprietary innovation with showing low intrinsic value. Both network effects and cointegration were seen to show significant results against here proposed Modified Information Ratio that introduced as the measuring tool to assess ICOs in this study.

The impact of the network effects may be considered to have fundamental value, which is widely discussed as being absent in the crypto assets. The ICO is an innovative fundraising method to raise funds for digital organisations for which this otherwise remains to be challenging. Auxiliary findings corroborate the organisational transparency factor to the ICO asset raising success, but also that the higher number of online business connections contributes positively to the ICO asset raise. However, the higher amount of business connections by the team members do not translate to a positive effect on the long-term success of an ICO, but reverse. This has implications on ICOs management of resources planning. Noting that the ICOs may only have used a platform such as ethereum to issue tradable tokens to facilitate their fund raising. The sponsoring of undeveloped goods will not expectedly create real network effects, but conversely, the ICO asset raise onto existing blockchain will show network effects due to its utility to users and the added externality. The existence of network effects factor is also important for an investor, as there was no indication of investor preference over whether the ICO organisation had already their own proprietary blockchain. The own proprietary blockchain had no impact on long-term performance either until it was interacted with ICO assets raised. In this sense, the technology enabled the network effect formation.

Appendices 2

Figure 1

Frequency display of words extracted from ICObench database ICO introduction fields. The features are taken from the ICO introductions. The percentage is computed from the total observation number of 675 ICO sample.

Key words in the ICO introduction	N	%
Blockchain	488	72%
Platform	362	54%
Decentralized	223	33%
Technology	196	29%
Network	187	28%
Data	179	27%
Users	176	26%
Token	166	25%
Digital	149	22%
Smart	144	21%

Appendix 2 Figure 2

Frequency display of male occupational title words from ICObench database team data.
The percentages are computed from 5,346 male team member sample.

Key words in the occupational title	N	%
Developer	660	11%
Co-Founder	502	9%
CEO	468	8%
Engineer	364	6%
Blockchain	363	6%
Founder	327	6%
Manager	317	5%
Director	285	5%
Chief	255	4%
Lead	254	4%

Appendix 2 Figure 3

Frequency display of female occupational title words from ICObench database team data.
The percentages are computed from 1,001 female team member sample.

Key Words in the occupational title	N	%
Manager	161	16%
Marketing	91	9%
Head	66	7%
Director	60	6%
Co-founder	59	6%
Developer	49	5%
Community	45	4%
Business	40	4%
Designer	38	4%
Development	36	4%

The percentages are computed from 1,001 female team member sample.

Appendix 3 Cointegration test

1. Testing for the Unit Root

The ICO -, ethereum - and bitcoin log-transformed daily price timeseries are tested separately for a unit root at 1% significance. Then Augmented Dickey-Fuller test is applied with fixed lags of 2, as there were 675 individual ICOs to test and the use of e.g. the Akaike information criterion (Akaike, 1969, 1971 and 1974) (hereafter AIC) would produce differing lags. This could make the results more complex to compare as the ICO's time periods are different.

The individual tests results show that unit root is present with 609 ICO -, ethereum - and bitcoin timeseries. The rest of the ICO sample [N:66], which do not exhibit a unit root, is ignored.

2. Testing for the Cointegration

Johansen's cointegration eigenvalue test (Johansen, 1988) is then employed to 609 non-stationary ICO daily timeseries with ethereum and separately with bitcoin at 5 % significance. The Johansen eigenvalue test was used as for its comparably higher robustness over the Johansen trace test in treating smaller samples (Lütkepohl, et al. 2001). Whilst the mean trading day is 536 days, the standard deviation is 270 days. The trend is also applied here due to the ICO sample's mean annualised return of -248%. The AIC is used to determine the lag length for the ICO and ethereum or bitcoin cointegration test with a maximum lag set to 20. The test statistics are compared with the critical values drawn from Juselius (2006). The results show that 100 ICOs have a cointegration relationship with ethereum and, separately, 86 ICOs present a cointegration relationship with bitcoin at 5% significance.

The results are made into dummy variables for all the ICOs observations [N:675].

Chapter 6: Summary of Essays: Findings, Conclusions and Recommendation

This PhD thesis presents four novel inquiries into the demand for blockchain-based alternative financial instruments. The empirical studies specify, or alternatively, calibrate the new form of methodologies and data acquisition methodologies. This contribution is important due to high frequency financial data combined with the new forms of digital assets value drivers. FinTech, whilst interdisciplinary topic, should also be studied as part of social sciences. This study utilises survey data on the motivations of retail investors to take up new FinTech base instruments. Price time series are empirically informative and can be used to assess challenging asset valuations, even for the volatile ICOs. The following sub-sections will individually summarise the contributions by starting this with a scholarly study and then three independent empirical studies.

The purpose of the Skills in Fintech essay was to build a foundation on the different new technological innovations in financial services and their required skill set. This also provides a brief definition and the scope of the research sub-field. These were also assessed in conjunction with incumbent financial service institutions. From the outset, the financial services already utilise a high amount of information technology. This remains a paramount and even more important consideration for skill requirements and employment in this industry. When systems are automated and scaled up with IT, these can substitute even human capital in tasks that have utilised cognitive skills. The chapter points to skills portfolio in these roles. Whilst the study finds a basis for the increase in necessary technological skills, it also emphasises the continuing need for ethics training in finance.

The aim of the financial literacy and attitudes in cryptocurrencies essay was to assess how the retail investors are adopting and perceiving the risk of these investments. Financial literacy is traditionally studied for its potential to contribute to the personal wellbeing. Financial literacy score of the populations is assessed against the adaptation of cryptocurrencies. This study utilised data from three surveys and included 18 countries globally. The study finds that individuals who have higher financial literacy and are more aware of risk and return expectations, are less likely to own cryptocurrencies. Nevertheless, individuals with higher financial literacy are more likely to have heard about these instruments.

The objective of the bitcoin futures and cash markets price discovery essay was to understand the older, such as the futures, and new FinTech innovation, such as the bitcoin, and their contribution to the common underlying market. Futures were evidenced to lead the cash markets in price formation on all studied frequencies using Granger causality, information share and component share tests. In this sense, the bitcoin futures were more efficient instruments and their provided more trustworthy pricing data from an established and regulated institution. These are also thought to have a higher concentration on relatively more informed traders. The informed trader would use the futures for information source for bitcoin price even though the trading volumes of futures were considerably lower compared to the cash markets. Due to the regulation of these future exchanges, there is a certainty that the exchange is not the counterparty for future contracts but a real market counterparty.

The Empirical study network effects in ICOs essay investigates ICO FinTech innovations by utilising price time series. The study attempts to evidence and measure the existence of network effects in ICOs, where this has been said to be the driver of their performance. The essay includes the novel use of modified information ratio and price cointegration basing on comparativeness of ICO assets to existing technology and network. Utilizing this information ratio, the study provides a novel tool for estimating the impact of network effects in the ICOs long-term performance with mitigating sentiment price drivers. Even though the ICO market has been considered volatile and noisy, the publicly traded timeseries convey asset quality signalling. Due to the missing data on self-reported ICO profiles in ICObench, the robust analysis based on their descriptive data is challenging. This is a consideration of the benefits and challenges of big data. However, there remain the benefits in the informativeness of the publicly traded and priced assets.

This study also attempts to investigate the human capital element in these organisations. This is a continuation of assessment of human capital from the first essay that focused on mostly incumbent, banking organisations. Whilst business networks are important for the asset raising and marketing in the ICO fundraise, these also may have negative impact on the development of the innovation. The technical skills are important part of these organisations' human capital.

6.2 *Implications of the study*

Finance is part of social science research field; it is not possible to form a view of a new market/place without understanding the dynamics of the initiatives in real economy that might require funding. Whilst technology innovation prompts science knowledge in the usage in financial services, there is clarity arising from this study is that the finance discipline is part of the social sciences field. This is especially noticeable considering human capital such as the skills of employees in financial services, but also the skills and sentiment of financial service participants. The thesis highlights that technology is enabling but is not the leading factor in financial services. This also holds for FinTech.

Intuitively, financial services function for providing a framework to provide financing to ideas from people who have surplus of assets but may be lacking specific idiosyncratic ideas. Whilst finance study has been focusing on firms as agents, there also now organisations such as ICOs that their decision making may be centralised or decentralised when they innovate and provide growth with their research and design. There are practical considerations related to investing in these digital assets. The understanding in long-term network effects instead of e.g. short-term sentiment, might help small and mid-sized digitalisation focused companies to prove their value and find funding.

When considering the policy implications, the foremost need to protect retail investors is clear. The blockchain technology that underpins ICOs has potential, but regulation, e.g., in relation to marketing, is needed to support the investors or the user base. Also, whilst these instruments require higher digital skills, they can aid in financial inclusion with improved access to financial services. Digitalisation facilitate cost effectiveness, and these instruments open a new investor or saver base that otherwise might not be able to invest with traditional investments such as equities or bonds. And that this way of funding facilitation can reach small and mid-sized organisations that otherwise would not have access to it. Already, countries with large relatively young populations such as

India and China show higher participation using fintech in payments or investing using fintech with no or a relatively moderate gender gap (Chen et al., 2021).

Relating to workplace inclusion in financial technology, according to the ICO team description statistics as exhibited in chapter 5, there were only 17% women working in ICO organisations on average. In addition, the female job titles were also perceived to be less senior in comparison. The presumption can be made that those roles have also lower remuneration plans. As discussed in chapter 2 about skills education that are suited for the roles in fintech. Education in these skills inclusively, can help with both increasing gender inclusion and increase remuneration through access to more senior roles.

6.3 Limitations of the study

The attitudes to cryptocurrencies and financial literacy study use data from18 countries globally, but it also utilises a proxy of financial literacy scoring for 15 of them. Whilst this study combines micro and macro data, it may be improved with respondent level preference observation data.

Volume is an important indicator of price development in price discovery and asset price development. Considering the bitcoin futures and cash market price discovery, the study utilises only a static, snapshot of trading volumes when compare futures and cash markets and does not take into account the trading volumes. Similarly, in the following study that investigates the ICO network effect, this study considers the initial coin offering assets raised. For both studies, the presumption is that the asset volatility development will contain information on the trading volume.

6.4 Future research

Relating to this study, it would be interesting to further examine the potential insights in cryptocurrency retail investing behaviour by using data from the advanced financial knowledge set of financial literacy questions (van Rooij et al, 2011). These advanced set of questions are specifically useful in assessment of retail investing knowledge and behaviour. This study could also inspect retail investors' sentiment driven behaviour against this extended financial literacy measure. The basic financial literacy questions relate to every day financial interaction, knowledge and behaviour.

Also, an extension study could be made on the demand side of ICOs to discover more of the motivations of retail investors. The presumption is that whilst there are short term investors, there are also long-term investors. Whilst the long/term investors might be motivated to diversify their existing portfolios from equity, bonds, real estate, gold, there also might also be investors that otherwise would do not invest their savings. In other words, ICOs and digital assets may increase financial inclusion. If that is the case, what are the covariate indicators behind this behaviour? The assumption is that ICOs might be more regional before they may scale up to a global reach. It could be interesting to investigate this progress to better understand the scalability among countries that have different financial regulation regimes. This scalability of a FinTech organisation can also provide cheaper and more accessible financial services.

In addition, due to the online nature of the ICOs, their marketplace is very fitting for research into retail investor behaviour and into the concept of FOMO, fear of missing out, in digitalised financial services. FOMO sentiment marketing might have an impact in investment product selection; portfolio return and the opportunity cost. It raises the research question should something so inclusive be allowed to be sold as exclusive, especially when financial services for such as investing or saving is considered. Furthermore, if the marketing emphasises on both scarcity, time-limitations and high sales, this may disrupt the investors' study on the project quality itself. Also, are wealthier who already access to financial services targeted for such campaigns.

Generally, there are multitude future research avenues in FinTech, which can relate to following concepts as described as following. Comparing to traditional finance research, where agents such as central banks, banks, firms a consumers/savers/investor are the focus or units of the finance study, the FinTech sub-field includes platform cryptocurrencies, ICOs and users with their new dynamics and agencies. For instance, comparatively regulatory light FinTech peer lending companies are not able to create money like traditional banks through deposits and their central bank infrastructure and base their financing on investor risk pooling and matching. In cryptocurrencies, conversely, money creation process is conducted through mining. The FinTech companies may also use oracles when they match parties for foreign currency exchange without directly affecting the price discovery in the bank exchange platform networks.

Also, move to digital currencies were first adopted by consumers, which is usual for disruption. The expectation from theory of disruptive innovation is that institutions will follow, and this strategy relates heavily to management studies. Cryptocurrencies saw increasing attention by institutions at the end of 2020. That year also saw a global COVID-19 virus epidemic and general technical push to the cloud and digitalisation by replicating local or physical service digitally. This technological paradigm shift also make for opportunities for update research in financial study within the newer financial services environment.

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