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Who Are the Bitcoin Investors? Evidence from Indirect Cryptocurrency Investments[1]

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Abstract:
Cryptocurrencies have received growing attention from individuals, the media, and regulators. However, little is known about the investors whom these financial instruments attract. Using administrative data, we describe the investment behavior of individuals who invest in cryptocurrencies with structured retail products. We find that cryptocurrency investors are active traders, prone to investment biases, and hold risky portfolios. In line with attention effects and anticipatory utility, we find that the average cryptocurrency investor substantially increases log-in and trading activity after his or her first cryptocurrency purchase. Our results document which investors are more likely to adopt new financial products and help inform regulators about investors' vulnerability to cryptocurrency investments.

Keywords: Bitcoin, Cryptocurrencies, Structured retail products, Retail investors, Household finance, Investor behavior

JEL-Code classification: G50, G40, D14, G11, G15, G02

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I. Introduction

While cryptocurrencies have existed since the first mining of a Bitcoin in 2009 (George, 2016), these assets have only recently begun to gain widespread attention from media, individual households, financial institutions, governments and regulatory agencies.[2] With significant price growth and volatility, especially toward the end of 2017, an increasing number of individual investors have chosen to participate despite warnings from the European Banking Authority or national supervisory authorities advising against "buying, holding or selling virtual currencies" (European Banking Authority, 2014; European Central Bank, 2015).

Despite the growing interest of the wider public in this subject, cryptocurrencies remain underresearched (Cheah and Fry, 2015). A nascent literature has begun to consider the potential of Bitcoin as a hedging instrument and its role in portfolio diversification (e.g., Baur et al., 2018; Bouri et al., 2017; Brière et al., 2015; Dyhrberg, 2016), the role of these assets as currencies (Weber, 2016; Yermack, 2013), the emergence of price bubbles (Cheah and Fry, 2015; Corbet et al., 2018), and price developments in the market with regard to speculation and insider trading (e.g., Baek and Elbeck, 2015; Feng et al., 2017; Gandal et al., 2017; Griffin and Shams, 2018). Available evidence suggests that large volatility and trading volumes have also attracted retail investors to Bitcoins (Urquhart, 2018); however, information about the characteristics and behavior of individual investors who choose to buy and trade cryptocurrencies remains relatively undocumented. One reason for the lack of empirical research in this area is the inherently anonymous nature of cryptocurrencies. One of the greatest advantages, and criticism alike, is that individuals can hold, trade, or use these instruments without a direct link to a retail bank account or investment profile.

In this paper, we provide an initial examination of who invests in cryptocurrencies by exploiting trading data on cryptocurrency-related structured retail products.[3] These vehicles are issued by banks to offer their retail clients an indirect avenue into cryptocurrency investments, and they are available to both European and US investors. For example, the Bitcoin Vontobel

[2] Price growth and volatility, the default of Mt. Gox in 2014 (Gandal et al., 2017), hacker attacks on large cryptocurrency exchanges (Kölling, 2017) or people losing their computers and millions worth of Bitcoins with them (Lange, 2017) have also brought the topic closer to the attention of retail investors.
[3] We include both structured retail products and crypto-related shares in our analysis and generally refer to them as structured retail products. We refer to holders of these assets as cryptocurrency investors throughout the text.

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XTB/USD Tracker index largely mimics the price path of Bitcoin and can be purchased via traditional brokerage accounts.[4] One benefit of our approach is that our measure of cryptocurrency investment goes beyond the proxies used in the existing literature, which infer crypto-participation from sources of data such as Google Trend data or Wikipedia searches. While investors in our sample invest in these structured retail products and shares, rather than the cryptoassets themselves, they actively purchase an asset linked to the true risk and return structure of cryptocurrencies.

The purchase process for directly held cryptocurrencies is more complex and riskier than for these retail products. Individuals can lose their entire investment if the associated private key is lost or compromised. Indirect investments via structured retail products, in contrast, may be more convenient but have different tax implications in most countries and could attract different types of investors. As such, our analysis captures investors with a preference for cryptocurrency risk-return profiles, while at the same time excludes individuals who may not be averse to investing in an unregulated environment or who might have illegal motives (Foley et al., 2018).

We exploit administrative data on investors drawn from a random sample of customers of a large German online bank, and we characterize investors' holdings and trading of cryptocurrency-structured retail products. We present new evidence not only on the characteristics of cryptocurrency investors but also on their investment behavior. We identify 31 cryptocurrency-related assets in our sample and note that almost 85% of the value-based holdings are concentrated around three investment vehicles. Slightly more than 1% of our total sample of investors hold such assets, with an average value of 3,750 EUR. This value translates to approximately 13% of the average total portfolio wealth. To investigate the differences between investors who hold and refrain from cryptocurrency investments, we measure the characteristics and behavior of both groups prior to their initial investment decision.

Cryptocurrency investors have approximately 60% (30,826 EUR) more total assets under management (AUM) than noncryptocurrency investors in our sample. They also report twice the monthly income (3,056 EUR) of noncryptocurrency holders. As previously documented in academic research and the media, we also find that cryptocurrency investments is a male-dominated activity. More than 90% of cryptocurrency investors in our sample are male, compared to a baseline share of 75%.

[4] This example is shown in Figure 3.

We then turn to analyzing the behavior of cryptocurrency investors and document significant differences from the average retail investor. In contrast to the average retail investor in our sample, cryptocurrency investors are more active traders (9.0 versus 2.0 trades per month), and they also log into their brokerage accounts more than twice as often (82.5 versus 27.1 times per month). Cryptocurrency investors also compose their portfolios differently from the average investor. They are significantly more likely to hold single stocks, equity derivatives, and warrants in their portfolios. Plus, the conditional share of these products in total portfolio volume is also much greater than in the average sample portfolio.

Technology adoption is a strong determinant of cryptocurrency investments. Investors holding cryptocurrency investments are 2.9 times more likely to have used the mobile-banking or mobile-trading app offered by the bank in our sample. Usage of robo-advice services is, however, statistically unrelated to cryptocurrency investments. This outcome suggests that, while technology adoption is an important correlate of uptake, the type of technology is an important distinction – since cryptocurrency investors are more likely to actively manage their own portfolios.

We then leverage the time series dimension of our data to investigate investor behavior around cryptocurrency adoption. We find that the average cryptocurrency investor increases activity significantly after his or her first cryptocurrency purchase. The average monthly number of portfolio logins increases by 16.5 (approximately 20%) and the average number of securities in the portfolio by 2.4 (approximately 16%). Both changes are statistically significant at the 1% level. Importantly, these increases are not driven by trading activity of the cryptocurrencies themselves; rather, investors increase trading activity in other, non-cryptocurrency related assets as well. This is consistent with recent literature on anticipation and trading activity (Olafsson and Pagel, 2019; Sicherman, et al., 2015), and echoes findings on the trend-chasing and overtrading behavior of retail investors (Barber and Odean, 2007).

Finally, and perhaps of most interest, our goal is to analyze the past trading and portfolio selection behaviors of the cryptocurrency investors in our sample. We find that cryptocurrency investors are more likely to trade penny-stocks and stocks featured in pump and dump schemes (Leuz et al., 2018). They are also more likely to participate in other investment vehicles with high idiosyncratic risk, such as emerging market, biotech, and solar-related ETFs. Comparing the portfolio return profiles of cryptocurrency and noncryptocurrency investors, we show that cryptocurrency investors have higher portfolio betas but lower portfolio efficiency, as measured by

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relative Sharpe ratio losses (Calvet et al., 2007). While the previous literature suggests that cryptocurrency can be used as a diversification instrument (Bouri et al., 2017), the cryptocurrency investors in our sample might underperform due to investment biases. We demonstrate that cryptocurrency investors are more prone to traditional investment biases, such as trend chasing and lottery-stock preferences.

In summary, our findings point to a certain type of retail investor who participates in cryptocurrency investments, namely, one that is an early adopter of financial and technological innovation and who has experience with high investment risk. From the perspective of policy-makers, this type of investor can be considered less vulnerable than the average retail investor.

While we use a measure for investors who hold an asset tied to the price development of a cryptocurrency, the investors in our sample are not necessarily direct investors in cryptocurrencies. It is reassuring, however, that the demographic profile of our indirect cryptocurrency investors echoes survey-based studies of Bitcoin investors, which find similarly high shares of male investors and high-income individuals. However, according to these studies, direct investors seem to be younger (60% younger than 35 years old), and direct investments seem to be larger with shares ranging between 10,000 USD and 50,000 USD invested across a few different cryptocurrencies (ARD Börse, 2018; Coindesk, 2015). Our findings, therefore, provide a clear contribution to the literature by providing an examination of investors' portfolios, investment choices, and biases using detailed transaction-level data.

Cryptocurrency-based structured products are likely to become more prevalent in the market over time. While an ETF variant was rejected by the Securities and Exchange Commission at time of writing (Securities and Exchange Commission, 2018), the first Bitcoin future was introduced on a public exchange in December 2017, and several such new vehicles are about to be launched (Huillet, 2018). In addition, the popular US-based trading app Robinhood has recently unveiled cryptocurrency trading without commissions (Nikhilesh, 2018). As these developments contribute to further establish cryptocurrencies in the broader investment population, understanding the characteristics and behaviors that predict investments in these asset classes remains an important and topical area of research.

The consumer side of cryptocurrencies, however, remains understudied, mainly due to the anonymity of the Bitcoin network, in which only "addresses" but not "users" are identifiable, and this constitutes as our main contribution. Bohr and Bashir (2014) use the publicly available

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survey data by Smyth (2013),[5] showing different indicators that positively affect Bitcoin accumulation, namely, age, early adoption and mining, spending Bitcoins on illicit goods, and participating in Bitcoin-specific forums. A contemporaneous paper by Hasso et al. (2019) uses data from a contract of difference (CFD)[6] broker to identify demographic characteristics, trading patterns and the performance of cryptocurrency investors. Our work, in contrast, uses a considerably broader dataset that not only focuses on a specific, high-risk product class but also allows us to compare cryptocurrency and noncryptocurrency investor behaviors across a wide investment spectrum and time series. In addition, we measure the returns of the entire portfolio and are able to investigate investment biases and the adoption of financial innovation. Only a few studies, such as Foley et al. (2018) or Meiklejohn et al. (2013), have transformed individual transaction data into user-level data via the Union-Find algorithm (Cormen et al., 2009).[7] However, extending the knowledge on cryptocurrency investors is important for two reasons. First, if Bitcoins are attractive to new users mainly because of their investment features, as documented by Glaser et al. (2014), then understanding the characteristics of new retail users contributes to the finance literature on the investment behavior of households, the biases and mistakes they make (Barber and Odean, 2013; Campbell, 2006), and the role of news and the media in attracting investors to investments (Barber and Odean, 2007; Dorn and Sengmueller, 2009; Dorn Jones et al., 2015). Furthermore, investments in risky assets may translate into individual (negative) experiences, and particularly for novice investors are likely to affect their future financial decision making (e.g., Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2008; Andersen, Hanspal, and Nielsen, 2019).

Second, we contribute to the literature on the use of structured retail products. The previous literature has provided details about the characteristics of users (Abreu and Mendes, 2018)

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[5] Smyth (2013) posted a survey link on different Bitcoin websites and found that the average user of the network is male (95.2%), 32.1 years old has a full-time job (44.7%) and is in a relationship (55.6%). Curiosity and profits are the main reasons to participate. However, this survey suffers from self-selection bias and a small number of participants, and the authenticity is difficult to verify.

[6] Contracts of differences (CFDs) are contracts in which the seller agrees to pay the buyer the value difference between the current value and contract time value of an asset. Due to their highly speculative nature, the European Securities and Market Authority has restricted the marketing, distribution and sales of CFDs several times to retail clients, especially with regard to leverage limits (2:1) for cryptocurrency CFDs (European Securities and Markets Authority, 2018).

[7] This algorithm allows for identifying addresses connected to a single user, making it possible to link each transaction to the associated users. Although this algorithm is widely used, it does not have perfect accuracy.

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and their rationality and risk preferences (Fischer, 2007; Kunz et al., 2017). Our focus on cryptocurrency-related structured retail products adds insight into products only recently introduced to the marketplace.

From a practical point of view, our analysis sheds light on how new technologies and investment strategies are adopted by different types of consumers over time. Understanding these uptake patterns is important for policymakers, as well as the financial sector. From a consumer financial protection and normative point of view, it is important that research investigate the financial outcomes associated with new product and technology adoption such that researchers, policymakers, and financial institutions can accurately measure the associated welfare gains or losses.

The remainder of our paper is structured as follows. In the following section we further describe the background of cryptocurrencies and the related literature. Section 3 provides an overview of the data. Section 4 describes our main results regarding the demographic and portfolio characteristics of cryptocurrency investors, their trading and banking behaviors, and their portfolio characteristics, as well as a pre- and postinvestment analyses. Section 5 concludes the paper with an outlook for further research and implications for regulators.

II. Background and hypothesis development

a. *Background and related literature*

Nian and Chuen (2015) describe cryptocurrencies as "…a peer-to-peer version of electronic cash. It allows online payments to be sent directly from one party to another without going through a financial institution. The network time-stamps transactions using cryptographic proof of work." The European Central Bank, in contrast, defines cryptocurrencies as a "…digital representation of value, not issued by a central bank, credit institution or e-money institution, which in some circumstances can be used as an alternative to money" (European Central Bank, 2015). Inherent in the latter definition is the view that cryptocurrencies are not a form of full money as defined by the economic literature or from a legal perspective (European Central Bank, 2015). In May 2019, there were "more than 2,000 cryptoassets with a total market capitalization of approximately 230 billion EUR" (Euro area statistics, 2019). The most famous and successful cryptocurrency and that with the highest market capitalization, at the time of writing, is Bitcoin (Bonneau et al., 2015).

Bitcoin was introduced in 2008 by the pseudonymous Satoshi Nakamoto (whose identity is still unknown) and has been operational since the mining of the first Bitcoins in 2009 (Weber, 2016). Bitcoin is a network that allows virtual Bitcoins to be transferred anonymously between users without going through a central institution. In addition, Bitcoin is free of legal or governmental control (Baur et al., 2018). All transactions are verified and logged decentrally by all computers in the network (Weber, 2016). If consensus about the legitimacy of the transaction is reached by the decentral network, a new block is added to the chain of registered transactions – the so-called blockchain. Hereby, the potential problem of double-spending Bitcoins is solved (George, 2016) since the chain cannot be changed and is therefore immune to manipulation (Glaser et al., 2014). New Bitcoins are generated by the process of mining, and the maximum number is limited by design to 21 million (Bouri et al., 2017; George, 2016). The "miners" generate new Bitcoins by successfully solving cryptographic problems and validating transactions (Brière et al., 2015). By this process and protocol-based scarcity, Bitcoin mimics the behavior of natural resources. Proponents of Bitcoins regard it as a an alternative and challenge to existing government-backed currencies – of particular interest after the recent financial crisis (Cheah and Fry, 2015).

The characteristics of Bitcoins have both advantages and disadvantages. On the one hand, Bitcoin poses a challenge to existing payment solutions on the internet due to its cost structure, global reach and anonymity, as the European Central Bank (2015) argues. In addition, Bitcoins allow for fast and inexpensive transactions and can thus spur financial inclusion (European Banking Authority, 2014). On the other hand, the European Banking authority alone has identified more than 70 risks associated with Bitcoins (European Banking Authority, 2014). The absence of government control and strong anonymity allow for money laundering and black market activities (Baek and Elbeck, 2015). In addition, the dependency on IT and networks is high, the spread of payment acceptance is low, and volatility and the risk of fraud are high (European Central Bank, 2015). At the moment, users are not protected against these risks (European Central Bank, 2015). Foley et al. (2018) further emphasize the need for regulation by showing that approximately 25% of all Bitcoin users and 44% of transactions are associated with illegal activity.

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Since 2009, Bitcoin has generated much interest in the media and the wider public and has established itself as the leading cryptocurrency (European Central Bank, 2015). Despite the bankruptcy of the Mt. Gox exchange in 2014, hacker attacks, and the decision by the Chinese government to close Bitcoin exchanges (Wildau, 2017), prices of Bitcoins increased dramatically from 2013 until 2017, with significant volatility (Figure 1). At the beginning of 2013, a Bitcoin was worth approximately 130 USD, it was worth 960 USD at the end of 2016, and it was worth approximately 14,000 USD at the end of 2017. In 2017, the prices grew at a record high, with a compound annual growth rate of approximately 1,300%. This occurrence sparked public attention and large inflows from private investors – despite warnings of an emerging bubble (Baur et al., 2018; European Banking Authority, 2014; European Central Bank, 2015), and it is potentially at odds with the notion that Bitcoins have no intrinsic value (Christopher, 2014). The value of Bitcoins arises only because users believe or speculate in its value. Additionally, academic papers conclude that there is evidence of bubble behavior with Bitcoins (Corbet et al., 2018). Since the beginning of 2018, prices have again declined and are oscillating around 4,000 USD as of the end of 2018 (CoinMarketCap, 2018).

Regulatory action to regulate Bitcoins has so far been scarce. The European Banking Authority issued a warning to consumers in 2013 about the risks associated with Bitcoins. This warning was renewed in 2014, and banks were asked to discourage customers from buying, holding or selling Bitcoins (European Banking Authority, 2014). However, no formal regulation exists at the moment in Europe, partly because the European Banking Authority estimates that a "regulatory approach to address these risks would require a substantial body of regulation" (European Banking Authority, 2014).[8] Worldwide regulations also differ. Some countries have undertaken strong measures, while other have attempted to expand banking regulations to cryptocurrencies. China, for example, forbids initial coin offerings (ICOs) and exchanges as well as mining operations. The sale and purchase of cryptocurrencies are also banned in India and some other Asian countries as well as in Bolivia and Morocco. In South Korea, people can trade on

[8] In Germany specifically, the Bundesanstalt für Finanzdienstleistungsaufsicht has classified cryptocurrencies as financial instruments according to § 1 Clause 11 Sentence 1 Kreditwesengesetz (Bundesanstalt für Finanzdienstleistungsaufsicht, 2017a), officially warning consumers not to participate in so-called initial coin offerings (Bundesanstalt für Finanzdienstleistungsaufsicht, 2017b), which are basically a crowd-funding instrument for companies with a cryptocurrency business model. In addition, the Deutsche Bundesbank has warned consumers in several interviews (European Central Bank, 2015).

exchanges, but only with real names and once their identities have been verified. In most Western countries, banking authorities warn about the risks; however, the activities are still legal (The Law Library of Congress, 2018).

Considering the speculative nature of Bitcoins and the warnings from regulators, analyzing the characteristics of Bitcoin investors is important for at least two reasons. First, it is a natural contribution to a large literature on individual investor behaviors and the associated biases that on average reduce consumer welfare (e.g., Barber and Odean, 2013, 2000). Second, understanding the characteristics of investors likely to participate in these types of new product offerings can help to identify investor groups that might benefit the most (or least) from policy reform or private solutions, such as financial advice.

b. *Individual retail investors and hypothesis development*

Currently, little is known about the users and investors of Bitcoins and other cryptocurrencies, mainly due to a lack of systematic data collection and costs associated with identifying users (Yelowitz and Wilson, 2015). Hasso et al. (2019) find that men are more likely to trade cryptocurrencies. In addition, early work has suggested that individuals hold Bitcoins mainly as a currency or for fun (Grinberg, 2012). In contrast, survey data suggest that many users use Bitcoins for investment purposes (Bohr and Bashir, 2014; Smyth, 2013), and new users keep Bitcoins in their wallet for extended periods of time (Glaser et al., 2014). It is likely that the price increases in 2016 and 2017 further enhanced the number of users who purchase Bitcoins to achieve high investment returns. This effect is also observed by Hasso et al. (2019). Therefore, it is important to analyze the effects of introducing Bitcoin investment into the portfolios of private households.

Currently, there are two main ways to invest into cryptocurrencies: direct investments over online exchanges and storing them in wallets[9], or indirect investments via structured retail products, which can be bought via existing brokerage accounts. Most importantly, and as evidenced in Figure 3, the tracking error of indirect investments over direct investments is minor, and the

[9] Directly purchasing cryptocurrencies involves registering on a web exchange (Nian and Chuen, 2015), sometimes additional legitimation, the currency exchange to Bitcoin and other cryptocurrencies, the decision for a web, app or paper wallet to store the cryptocurrencies and the need to store the private key. This process can be associated with a time delay of several days and often inadequate user experience. Reports of hacker attacks or losses due to lost private keys or changes in phones/laptops in the media (Kölling, 2017; Lange, 2017) might further spur the fear of private investors and hinder investments.

return profiles are therefore very similar. However, there are also differences: indirect investments are typically associated with greater convenience for the investor since no additional technical knowledge or additional tools are required. While transactions costs are often lower than trading the underlying directly (Fischer, 2007), they often come with management fees, overpricing, and additional premiums (Bergstresser, 2008; Bernard and Boyle, 2009; Jørgensen et al., 2012). Any capital gains from indirect investments are fully taxed by a flat tax of 25%, whereas at least in Germany, gains from Bitcoins are tax-free after a twelve-month holding period, respecting the first-in first-out principle and losses are deductible from taxes if occurring in the first 12 months. In other countries, the tax regimes differ. For example, in Israel, cryptocurrencies are treated as assets and in Switzerland as financial assets. In Argentina and Spain, they are subject to income tax. The same is true for Denmark, where also losses are deductible.

Many studies have shown Bitcoin's specific characteristics as an investment vehicle. Analyzing the volatility of Bitcoin, Yermack (2013) argues that the behavior of Bitcoin resembles more a speculative investment than a currency. This finding is confirmed by Baek and Elbeck (2015). Comparing Bitcoin and S&P 500 returns, they show first that the return on Bitcoin is much more positively skewed than that on stock returns. Second, they show that price changes of Bitcoin are difficult to reconcile with any economic fundamentals, demonstrating an important role of speculation and/or sentiment in price formation. In line with this finding, Liu and Tsyvinski (2018) find that cryptocurrencies have very different risk-return tradeoffs compared to stocks, currencies, and precious metals and that their returns are rather determined by strong time-series momentum and investor attention. Feng et al. (2017) find a sensitivity to regulatory and market events. The speculative nature of the market is confirmed by the evidence of informed trading (Feng et al., 2017) and evidence of price manipulation (Griffin and Shams, 2018). Despite their speculative nature, there is evidence that cryptocurrencies have positive portfolio effects, at least over their short period of existence. Baur et al. (2018) find that returns from Bitcoin are uncorrelated with stock and bond returns – in regimes of both low and high market volatility. Dyhrberg (2016) confirms that Bitcoins allow for hedging against the Financial Times Stock Exchange Index and to some extent also against exchange rates. Brière et al. (2015) go so far as to conclude that US investors should hold a portion of their wealth in Bitcoin because doing so would substantially improve the risk-return profile of their portfolios. Bouri et al. (2017) document smaller diversification effects, but in summary, the literature suggests that cryptocurrencies might play an important role in the portfolio selection of individual investors.

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Despite the positive effects of structured retail products, e.g., by offering access to assets otherwise not available to private investors or offering different payoff profiles (Fischer, 2007), they come with disadvantages. Some are sold at a significant premium (Abreu and Mendes, 2018; Bergstresser, 2008; Bernard and Boyle, 2009; Jørgensen et al., 2012), are increasingly complex (Celerier and Vallee, 2017), or have attractive advertised yields of approximately 12% p.a. but negative expected returns, such as the case for yield-enhancing products (Vokata, 2018).[10] Therefore, researchers (e.g., Abreu and Mendes, 2018; Döbeli and Vanini, 2010; Fischer, 2007) suggest that the demand for such products is difficult to explain with normative theories and can be rather attributed to behavioral biases or misselling.

Due to the risky nature of cryptocurrency investments, they can attract similar investors as lottery stocks (Kumar, 2009) and penny stocks (Leuz et al. 2018) – individuals who like to gamble (Dorn Jones et al., 2015) or who see trading as entertainment (Dorn and Sengmueller, 2009). Kumar (2009) finds that mainly younger, less wealthy, less educated, and nonprofessional single men invest in lottery-type stocks, while Dorn Jones, Dorn, and Sengmueller (2015) show that male, blue-collar investors are more likely to gamble than other investors.

Since Bitcoin is technology-related, it is worth considering the characteristics of early adopters of technology. Several studies have found that men are more inclined to adopt new banking technology than women (e.g., Akinci et al., 2004; Pijpers et al., 2001; Wan et al., 2005), and middle-aged customers use internet banking more than younger customers (Akinci et al., 2004).

Based on the extant literature, we hypothesize that the average cryptocurrency investor will be male, middle-aged and an early adopter of technology. It remains ambiguous whether cryptocurrency investors are also more likely to be blue-collar workers and less educated or whether they attract a higher wealth clientele. In addition, we presume that cryptocurrency investors have more trading experience, trade more frequently, especially in assets with high idiosyncratic risk and skewed return profiles and have riskier portfolios than the average individual investor.

[10] These products combine both high-coupon bonds and short positions. Often, the fees are not transparent to the investors and cannot be calculated without complex methods.

III. Data

We obtain data from a large German online bank that offers the full range of banking services to its clients, including checking and savings accounts, consumer loans and mortgages, brokerage services and investment advice via telephone and fully automatic solutions (robo advice). Across the sample, advice is only used sparely (4% telephone, 3% robo). Most clients are thus do-it-yourself (DIY) investors. We use a dataset on client transactions and account balances similar to others in the literature, e.g., Bhattacharya et al. (2012). Our initial dataset contains records on approximately 258,000 randomly selected clients from January 2003 until September 2017, together with sociodemographic client data, such as gender, age, ZIP code, etc. We exclude all customers who do not own a securities account or have missing information (some 116,000 clients) or who do not show any trading behavior (some 42,000 clients) over the observation period. This process leaves us with approximately 100,000 investors for our main analyses. We winsorize total and portfolio wealth, as well as the number of total logins, at the 1st and 99th percentiles.

We generate a list of traded ISINs containing the words "Bitcoin," "BTC,"[11] XBT,"[12] "Ethereum," "ETH,"[13] or "Ripple." These three cryptocurrencies had the highest market capitalizations at the time of writing and therefore, arguably, the most attention from retail investors (CoinMarketCap, 2018). In addition, we conducted a search on the social trading platform Wikifolio for cryptocurrency-related structure products. Wikifolio permits amateur and professional traders to design and launch structured retail products with a proper ISIN that mimics their own trading strategies and then to attract retail investors to purchase these products through their own brokerage. In total, we identify 31 cryptocurrency-related securities purchased by at least one sample investor between 2014 and 2017. A short description of the securities can be found in Table 10 in the appendix.[14] While some of those securities include shares, most are structured retail products issued by XBT Provider, an issuer of exchange traded cryptocurrency products, Vontobel, a Swiss financial services company and a large structured retail product issuer, and Lang & Schwarz, an issuer of structured retail products on the social-trading platform Wikifolio.

[11] BTC is a commonly used abbreviation for Bitcoin.
[12] XTB is the unofficial currency code compatible with ISO 4217, used by some exchanges.
[13] ETH is a commonly used abbreviation for Ethereum.
[14] Description for ISINs related to certificates can no longer be found after the last trading date. ISINs of closed products are issued to new products.

Some of these products come with high fees of up to 2.5% p.a. All investors who traded one of the relevant securities at least once are flagged as cryptocurrency investors, yielding 929 clients, of whom 717 hold cryptocurrency-based securities in their portfolio for more than one month. Figure 2 shows the number of cryptocurrency investors[15] and their holding volume between 2016 and 2017 and indicates that activity soared in 2017, and monthly holding volume peaked at approximately 3 million EUR in September 2017. This period also coincided with a surge in Bitcoin price and media coverage.

The representativeness of our sample is limited in two dimensions. First, selection into the online bank is nonrandom, and there are many more self-directed investors in the sample than in the general investor population. Second, we scrutinize individuals who invest in cryptocurrencies indirectly through structured vehicles but not necessarily directly in Bitcoin at all. However, we have a real measure of investors that hold assets that offer the return profiles of cryptocurrencies (Baur, 2013). In contrast to the proxies used so far (e.g., Bohr and Bashir, 2014; Yelowitz and Wilson, 2015) ,[16] our measure is a tradable asset and is linked to financial behavior similar to the proxy used by Hasso et al. (2019). Nevertheless, direct investors might still be somewhat different in characteristics. Direct investors are likely to be even more technologically savvy and less sensitive with respect to high setup and transaction costs and with respect to legal and operational risks than indirect crypto investors. Finally, we cannot exclude that some our sample investors also invest directly into cryptocurrencies. However, our main results would only be biased if direct participation were more common among sample investors with no indirect cryptocurrency investment, which we find highly unlikely.

IV. Results

a. *Who are the cryptocurrency investors?*

The first step of our analysis is to investigate comparative descriptive statistics of cryptocurrency and noncryptocurrency investors. Since the data are an unbalanced panel (i.e., investors can enter and drop out of the dataset at different times across the sample period), we compute

[15] Excluding investors who trade cryptocurrencies within a single month and do not hold them in the portfolio
[16] Proxies in the literature include e.g., Google Trend data with anecdotal evidence or a combination of Wikipedia searches and Bitcoin events.

for each investor the average value for the last 12 months available in the dataset. Table 1 summarizes the descriptive statistics. Focusing on time-invariant demographic characteristics, 90% of the cryptocurrency sample is male, compared to only 75% of the baseline sample. In addition, cryptocurrency investors are more likely to use the sample bank as their main bank (48% vs 36%).[17] This finding is consistent with Wan et al. (2005), Pijpers et al. (2001) and Hasso et al. (2019), who find that men have a greater propensity to adopt online and mobile banking than women.

Cryptocurrency investors have significantly higher wealth in terms of total AUM at the bank than noncryptocurrency investors. Their income is also significantly higher (+3,056 EUR).[18] The average income is similar to that in the studies of Smyth (2013) and Coindesk (2018; 2015). However, the studies differ significantly in the age of the average cryptocurrency investor. While investors in our sample are on average 47 years old, the former studies report an age younger than 35, and Hasso et al. (2019) report the age group 35-44 to be most likely invest in cryptocurrencies indirectly. One reason for this age differential could be that younger people are perhaps more tech-savvy and therefore invest in Bitcoins directly, while older investors find it more convenient to invest indirectly in cryptocurrencies.

Table 2 summarizes the univariate differences between cryptocurrency and noncryptocurrency investors with regard to investment experience and portfolio characteristics. While the sample already has high login rates of approximately once per day (27.1 per month) – most likely due to the high proportion of DIY customers at the sample bank – cryptocurrency investors log into their online banking even more frequently (82.5 times per month). This finding suggests that they have a greater interest in their financial situation and that they perhaps view investment as an entertainment activity, a hobby, and/or even as a profession. They also participate to a significantly higher rate in stocks, derivatives, and warrants than their noncrypto peers. Portfolio underdiversification is measured with the Herfindahl-Hirschman Index (HHI), as used in the literature, e.g., by Dorn et al. (2008). Since a lower HHI indicates less portfolio concentration, the results suggest that the portfolios of cryptocurrency investors are significantly better diversified (0.25 vs 0.32). This finding is likely to be driven by the large number of assets in their

[17] Main bank is an indicator equal to one if a customer allocates at least half of the German tax exemption limit to this bank.

[18] Our income proxy is derived from the annual mean of the monthly difference between the highest and lowest checking account balances.

portfolios. Cryptocurrency investors hold more than twice as many securities as noncryptocurrency investors (15.1 versus 6.9) and especially a significantly larger number of single stocks (9.7 versus 3.6).

In line with the higher login rates, cryptocurrency investors also trade more frequently. With, on average, 9.0 trades per month, they trade four times as much as noncryptocurrency investors. The share of stocks (62%) and derivatives (8%) in their brokerage portfolio is significantly higher, as is the average product risk of the vehicles in their portfolios (4.06).[19] With regard to their cryptocurrency investment, investors who hold cryptocurrencies for a period of more than one month in their portfolios hold approximately EUR 3,750 worth of cryptocurrencies and approximately 2.5 cryptocurrency securities with a portfolio share of approximately 13%. This finding implies that at least some retail investors view cryptocurrencies not only as play money but also as a sizeable fraction of their total investments.

In Table 4, we present multivariate logit regressions and report results with odds ratios. The dependent variable takes the value of one for cryptocurrency investors and zero otherwise.[20] We include geographic fixed effects at the two-digit ZIP code level to compare investors living in tight geographic clusters. Column 1 reports that men are more than two times more likely to become cryptocurrency investors. This outcome is significant at the 1% level and in line with the findings by Hasso et al. (2019). Additionally, age and main bank relationship increase the likelihood of becoming a cryptocurrency investor, while an increase in years with the bank reduces this relationship slightly. Adding further control variables, such as wealth and trade risk, explains approximately 10% of the variance in the specification. Column 2 shows that a high portfolio value increases the likelihood of becoming a cryptocurrency investor (1.3), supporting the view that Bitcoin is seen as a speculative investment for some. Investors with high portfolio wealth can increase the share of a very risky and speculative asset more easily. Higher wealth investors and households have also been shown to be more risk tolerant. That cryptocurrency investors are more risk seeking is evidenced by the finding that investors with high average product risk are more than four times more likely to become cryptocurrency investors. Both results are statically and economically significant.

[19] Product risk is measured by the bank on a scale from 0 (money market funds) to 5 (turbo certificates) for regulatory compliance reasons (MiFID II).
[20] We also run our analysis with penalized likelihood ("Firth logit") and find quantitatively similar results.

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So far, we have analyzed the cross-sectional characteristics of cryptocurrency investors. Now, we turn to an analysis in which we relate cryptocurrency investors to both past and future investment behaviors. Here, we estimate the following model:

$$Pr(y_{it} = 1 \mid \boldsymbol{x}) = \Lambda(\alpha_0 + \boldsymbol{x\beta} + \beta_1 CyptocurrencyInvestor + \delta Geo)$$

where y_{it} are various investment behavior outcomes, $\boldsymbol{x\beta}$ is a vector of control variables, and β_1 is our coefficient of interest and states the relationship between cryptocurrency investors and these investment outcomes. δGeo are geographical fixed effects at the federal state level Λ is a logistic link function suggesting that we estimate the model with nonlinear logistic regressions and report odds ratios. As in Table 4, logistic regression analysis might not be ideal to explain variables in rare events data (King and Zeng, 2001) due to a potential small-sample bias in the maximum likelihood estimation of the logistic model. However, our results do not suffer from this bias since our number of events and our number of events per explaining variable are sufficiently high. Nevertheless, we also run our analysis with penalized likelihood and find quantitatively similar results. As we examine the cross-sectional characteristics at the customer level using data collapsed from 2003 until the point of cryptocurrency investment (for cryptocurrency investors) or 2017 (for noncryptocurrency investors), we do not use time fixed effects in these analyses. Geographical fixed effects allow us to account for regional investments differences in Germany (Laudenbach et al., 2018); however, they also do not drive our results.

In Table 5, we test whether cryptocurrency investment is correlated with other product and technology adoption.[21] In Columns 1 and 2, the dependent variable indicates usage of a bank-owned mobile trading app and/or use of mobile banking. Cryptocurrency investors are indeed more likely (2.9) to use these mobile apps. The results are significant at the 1% level and include additional control variables.

In Column 3, the dependent variable takes the value of one for previous or contemporary usage of a bank-owned robo-advisor, suggesting a portfolio based on risk preferences and investment horizon. Interestingly, the use of robo-advice is not significant after including control variables. This result seems in line with the very active, DIY type of cryptocurrency investor. In

[21] For cryptocurrency investors, we only examine the pre-investment period to avoid reversed causality.

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total, Columns 1-4 in Table 5 suggest that cryptocurrency investors in our sample are more likely to use tech-related product offerings from the bank.

We are also interested in how past purchase behavior might predict investment in cryptocurrency products. We test this theory in Columns 5-8 by considering how cryptocurrency investment correlates with past incidence of trading in penny stocks or commodity ETFs. Commodity ETFs provide exposure to characteristics of commodities as an underlying asset without the need to purchase each constituent (Baur, 2013); therefore, they are similar in nature to the cryptocurrency-based structured products. As such, early investment in these assets when they were only traded by a small number of early adopters make them an important comparison. Column 6 of the table shows that cryptocurrency investors are 1.5 times more likely to also have been early investors (before 2010)[22] in any of the 20 largest precious metal ETFs. This result is significant at the 5% level, including control variables.

Examining penny stocks (Table 5) and lottery stocks (Table 7), we define penny stocks as stocks priced at less than 5 EUR (Leuz et al., 2018) and lottery stocks as stocks with a high idiosyncratic volatility and skewness. The penny stocks that we include in our analysis are featured in previous pump and dump schemes and are derived from Leuz et al. (2018). The correlation between cryptocurrency investments and penny stocks featured in pump and dump schemes is highly significant. Cryptocurrency investors are 2.7 times more likely to be previous investors in penny stocks, explaining 14% of the variance including controls. Our results suggest that cryptocurrency investors might be drawn to pump and dump stocks and add to concurrent research highlighting the prevalence of pump and dump schemes also existing in cryptocurrency markets and platforms (Hamrick et al. 2018).

In addition, Table 6 shows that cryptocurrency investors are also more likely to purchase ETFs from markets and sectors that were trend topics at a certain point in time and have a higher risk-return profile, including emerging markets, biotech and solar. All of the results are significant at the 1% level. These products fit the risk preference of cryptocurrency investors and show a certain sophistication and interest in investment topics.

b. *Investment biases and cryptocurrency investments*

[22] We choose 2010 since only 8% of all commodity ETFs holdings fall into the period of 2007-2010.

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Much has been written about individual biases and how investment behaviors of retail investors deviate from theory (Barber and Odean, 2013; Dorn Jones et al., 2015; Kumar, 2009). For our analysis, we focus on two biases, which we hypothesize to be relevant for cryptocurrency investors, namely, trend chasing and exhibiting a preference for assets resembling lottery stocks. The former describes the behavior that individuals often chase past performance (e.g., Dhar and Kumar, 2001; Sapp and Twari, 2004; Sirri and Tufano, 1998). The latter describes a preference for stocks with low prices, high idiosyncratic volatility and high idiosyncratic skewness – similar to lotteries (Kumar, 2009). We construct both the lottery stock and trend chasing variables as in Sapp and Twari (2004) and Kumar (2009) and described in Loos et al. (2014). Our hypothesis assumes that cryptocurrency investors have a greater preference for assets with high skewness and are more likely to chase trends, and we test this hypothesis by regressing cryptocurrency investment on indicator variables for previous incidence of investment biases in transactions before individuals invested in cryptocurrencies.

Table 7 presents the results. In Column 1, the dependent variable is an indicator of trend chasing. We define trend chasing similar to the previous literature and calculate the previous year's returns ending the day prior to the purchase for each security in an individual's portfolio. We then rank individuals based on the mean value of their total returns on all purchases. Individuals above the 75th percentile are flagged as individuals more likely to purchase assets that have experienced high previous returns. We note that individuals who hold cryptocurrency investments are approximately 3.5 times more likely to have such high trend-chasing preferences. These results also hold when we add additional control variables (Column 2). This result is intuitive since the prices of Bitcoin increased dramatically during our sample time frame (Figure 1). Individual investors in our setting are likely to expect that price trends continue (De Bondt, 1993); therefore, their optimism continues in bull markets. Another explanation at work might be "keeping up with the Joneses" or "fear of missing out." Bursztyn et al. (2014) show that media coverage and social learning are important factors in financial decision making.

Column 3 in Table 7 suggests that cryptocurrency investors also prefer stocks with high idiosyncratic volatility and skewness or lottery stocks. In a sense, this finding should not be surprising since we have shown that these investors are already likely to have held penny stocks. Our definition of lottery stock preferences is based on prior work and measures the share of the portfolio held in stocks with high idiosyncratic volatility and skewness. We define high lottery stock preference as holding a share of the portfolio in these assets greater than the 75th percentile across the sample. Lottery stock preferences are positively correlated with cryptocurrency investments. This correlation is significant at the 1% level when including additional control variables. That there is a greater propensity for cryptocurrency investors also fits the investments that they make investments in the energy/solar and biotech sectors. Kumar (2009) finds that lottery stocks have a higher concentration, particularly in these sectors, among others. Bali et al. (2018) show that investors with lottery-stock preferences overweight the probability of a higher payoff, and the resulting demand increases lead to higher valuations and lower returns in the future. This finding is in line with Barber and Odean (Barber and Odean, 2007), who argue that retail investors are more likely to buy attention-grabbing stocks due to limited availability of time and resources. It also applies to the cryptocurrency-structured products in the scope of the analysis.

In addition, Ang et al. (2009) show a negative relationship between returns and idiosyncratic volatility; i.e., high idiosyncratic volatility results in low future average returns. That the greater propensity of buying lottery-stocks negatively affects the performance of cryptocurrency investors is also evident from Figure 6. Reducing high idiosyncratic volatility could have significant, positive benefits. For example, Loos et al. (2014) show that reducing lottery stocks in the portfolio improves annual performance.

c. ***Portfolio activity and cryptocurrency investments***

One of our hypotheses is that active, self-directed clients are more likely to be early adopters of cryptocurrency investments. We have already provided indicative evidence pointing in this direction by showing the low correlation between robo-advice usage and cryptocurrency investments. Robo-advice provides portfolio recommendations based on risk-preferences and investment horizons. Given this fact, it is likely that it is less favored by investors who appreciate full autonomy over their portfolios. In Table 8, we regress cryptocurrency investment on outcome variables associated with an active, DIY approach to money management. In Columns 1-2, we investigate the number of average monthly online banking logins. Cryptocurrency investors have an additional 54.5 logins, which is twice the number of the average sample client. The number of logins is mainly associated with being male, having a joint account with a family member (multiple people having access) and having the online bank as a main bank (main vehicle for money management). The extremely high login rates could be a sign of sensation seeking since it can be argued that people logging in twice per day to check price developments in their portfolios seek not only information but also some sensation that comes with the information. As Zuckerman (1994) argues, "sensation seekers look for both intensity and novelty in experience."[23] This also is in line with research documenting the effect of media on (over-)trading (i.e., Barber and Odean, 2007).

In Columns 3 and 4, we investigate the average number of monthly trades that investors conduct. Cryptocurrency investors have significantly more monthly trades (7.2), compared to 2.0 for noncryptocurrency investors. This difference decreases slightly to 6.6 when controlling for demographic and wealth factors. Men trade more frequently in our sample, supporting the results of Barber and Odean (2001), who find that men trade 45% more than women. In Columns 5 and 6, we show that cryptocurrency investors hold 8.0 times more securities in their portfolios compared to noncryptocurrency investors. This difference decreases slightly to 5.3 when controlling for additional variables but remains significant at the 1% level.

Finally, we analyze how the portfolios of cryptocurrency investors differ before and after their first cryptocurrency adoption using a single-differences approach. These results are provided in Table 9 both including (Panel A) and excluding cryptocurrencies (Panel B). Since the sample in this analysis includes only cryptocurrency investors, we include individual fixed-effects absorbing time-invariant investor characteristics and year and month fixed effects to partial out time-specific trends. The coefficient on the variable *after cryptocurrency investment* in Table 9 states the average monthly differences for the periods before and after first-time cryptocurrency purchases. For Panel A, we note that average login numbers increase by 16.5, and the average number of securities in the portfolio increases by 2.4. Both changes are statistically significant at the 1% level. For Panel B, the increased number of securities is slightly smaller (2.0). We assume that the increase in logins indicates an increase in attention to market and price developments induced by the high volatility of cryptocurrencies. That investors may choose to increase portfolio logins and trading activity is consistent with Ostrich effects in financial decision making (Olafsson and Pagel, 2019; Sicherman et al., 2015), as well as models of anticipatory utility (e.g., Kőszegi and Rabin, 2009), and that investors may be drawn to and affected by investments more prominently discussed in media (Barber and Odean, 2007).

[23] Gherzi et al. (2014) find evidence for the so-called meerkats effect. Investors show increased attention after positive market returns for logins but not for trades. Similar effects are reported by Olafsson and Pagel (2019).

In Figure 4, we relate the cryptocurrency investors' single differences to a matched counterfactual group and analyze the pre-and postinvestment developments for average logins, number of trades, and number of securities. We match demographic information (gender, years with the bank, age group and federal state), portfolio characteristics (stock participation, portfolio value difference) and month and year. Across panels in Figure 4, we note that cryptocurrency investors increase portfolio activity significantly from pre- to postperiods, while for a counterfactual group of investors, these differences are modest at best. Both groups follow similar pretrends (although it is clear that the outcome variables in levels are significantly lower in the counterfactual group). We also rerun the analysis without cryptocurrency securities. In Figure 5, we find, examining the number of trades and number of securities, that even when excluding cryptocurrency securities, the postinvestment activity of cryptocurrency investors increases even in noncryptocurrencies, demonstrating a behavioral change induced by cryptocurrency investments.

While it appears that cryptocurrency investors seem to significantly alter their investment behaviors following their initial cryptocurrency purchases, we cannot exclude that the results might be confounded by unobservables that change in parallel with first-time crypto investments, such as risk attitudes or market expectations of investors. An investor could, for example, invest in Bitcoin exactly because he or she wants to increase risk exposure. Our results provide suggestive evidence of differences in investment behavior around initial cryptocurrency participation; however, we refrain from a causal interpretation.

d. *The diversification potential and returns of future cryptocurrency portfolios*

An important question is how the portfolio return and risk profiles of cryptocurrency and noncryptocurrency investors differ. To answer this question, we follow Calvet, Campbell, and Sodini (2007) to calculate monthly expected returns for each investor portfolio.[24] As a benchmark, we use a multiasset benchmark based on Jacobs, Müller and Weber (2014).[25]

[24] We use the return index, which is adjusted for dividends (i.e., assumes that dividends are re-invested) and stock splits, as well as discrete returns based on the total return index from DataStream matched to the ISINs in the dataset. For many cryptocurrency products, return data are not available in DataStream.

[25] Von Gaudecker (2015) shows that a global full equity index, such as the MSCI World, would treat investors with substantial bond shares in their portfolios "unfairly." Jacobs, Müller, and Weber (2014) derive a 60%-25%-15% portfolio allocation for stocks, bonds and commodities with equally weighted regional MSCI indices for stocks. This benchmark does not include cryptocurrencies.

Figure 6 shows the mean-variance figures for both cryptocurrency and noncryptocurrency investors and thus the risk-return tradeoff achieved by each investor group. It can be observed that both groups bear more investment risk than implied by the benchmark and that neither group is compensated through higher returns for this additional risk. Therefore, a large number of investors underperform the benchmark in terms of portfolio efficiency. A similar effect is observed for household portfolios by Calvet, Campbell, and Sodini (2007) and Von Gaudecker (2015). However, when comparing both groups, cryptocurrency investors exhibit even lower portfolio efficiency. These findings are confirmed by the results of Table 3, in which we report both the portfolio betas and two mean-variance measures of underdiversification: the return loss and the relative Sharpe ratio loss (Calvet et al., 2007). The table reports these figures for the end of 2016 to account for the time before most people invested in cryptocurrencies. Cryptocurrency investors have slightly higher betas than noncryptocurrency investors, in line with the greater use of risker products shown in Table 2. The difference is significant at the 5% level. The difference in relative Sharpe ratio loss is also significant at the 5% level. The Sharpe ratio of the portfolio of cryptocurrency investors amounts to 69% of the Sharpe ratio of the benchmark (Relative Sharpe Ratio Loss 31%). The value is slightly lower for noncryptocurrency investors.

V. Conclusion

Especially after the recent price rollercoaster, cryptocurrencies have attracted much attention from media, individual investors and regulators. In parallel, the number of individuals holding cryptocurrencies has increased markedly. As a consequence, analyzing the characteristics of these individual investors and examining their behaviors and biases are worthwhile exercises that should also be informative for policymakers and financial institutions alike. Furthermore, and more generally, understanding early cryptocurrency uptake is also informative regarding technology and financial product adoption for individual investors and households.

In this paper, we use administrative data from a German bank to analyze the personal characteristics and investment behaviors of indirect cryptocurrency investors by examining investments in structured retail products. We find that, compared to the general investor in our sample, cryptocurrency investors are to a greater proportion male, have higher portfolio wealth and use other innovative products and services of the bank. In addition, their portfolios and behaviors differ markedly from their peers, they log into online banking more frequently than noncryptocurrency investors, and they trade more often and hold more securities – in particular more single stocks. These differences, especially with respect to the number of trades and logins, become even more pronounced in the period after their first Bitcoin investment. We also find that cryptocurrency investors have higher portfolio betas and experience higher relative Sharpe ratio losses. This finding might be partly driven by investment biases since their portfolio choice is to a larger extent driven by behavioral biases, such as trend chasing and lottery-stock preference.

However, the results should be interpreted with care. Indirect investments, although tied to the price development of the underlying cryptocurrencies, are only a proxy for direct cryptocurrency investments. In addition, external validity might be limited by our sample stemming from a single, albeit large, German online bank. This validity comes with the caveat that the generalizability of our results is obviously limited. However, it is difficult to imagine that our characterization of individuals investing indirectly in cryptocurrencies would be drastically different from that of investors with similar assets in the United States or other European countries. Ideally, future research would leverage additional data sources on direct cryptocurrency investments. In addition, future work will likely have a longer time horizon into the future after the introduction of cryptocurrencies to investigate whether households also perpetuate investment biases in cryptocurrency assets.

Finally, additional research is needed with a focus on consumer financial protection and financial vulnerability as it applies to cryptocurrency-related fraud, participation in initial coin offerings (ICOs) and the link between cryptocurrency and crime. This focus is important since the regulation regimes differ widely across jurisdictions. Retail securities (offering indirect investments into cryptocurrencies) are subject to the full national and European consumer protection scheme, such as MiFID II, with three implications in our context (European Parliament, 2014). First, a target market must be defined by the product issuer, and the sales team must act in line with this target market definition. Second, products must be classified along seven risk classes, allowing for an EU-wide product comparison and ensuring that only customers with a risk preference in a certain product class can buy such products. Since structured products are classified in the highest risk class, they are only available to customers with a high risk-preference. Finally, products become more transparent as a wider variety of costs must be made transparent both ex ante and ex post. Due to the characteristics of indirect cryptocurrency investors in our analysis, no additional consumer protection policy seems to be required. Because of the high risk class classification, the products that we analyzed are only available to a small number of investors who do not require additional protection. Therefore, our findings seem to suggest that MiFID II works. However, consumers should be aware of the high product costs that they might incur when holding structured retail products. This risk contrasts with direct investments, which are currently completely unregulated, and reports about cryptocurrency-related fraud, especially with regard to initial coin offerings (ICOs), are still part of everyday news. Considering that direct investors might even be more vulnerable, e.g., lower income due to lower age and with the risk of total loss not only due to rate fluctuations but also due to hacking, fraud or technological issues, discussions on a regulatory scheme must progress, it could start with a better control and overview of the financial flows of online exchanges and trading platforms and standards and rules for ICOs. Since different European regulators treat cryptocurrencies differently, such regulation could occur at an EU level, also considering the single market for capital.

Our results contribute to ongoing research on household finance regarding biases and investment behaviors as well as potentially targeting consumer protection. Based on our results, cryptocurrency users are experienced investors with high portfolio wealth. While it is important that regulating authorities warn consumers about potential investment risks with cryptocurrencies, it seems that in our sample, investors do not belong to a very vulnerable group that necessarily requires additional consumer protection.

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Tables

Table 1: Descriptive characteristics

This table reports descriptive statistics on customer demographics of cryptocurrency and noncryptocurrency investors with security accounts in our sample. The last column reports the difference in means between the groups. *Total AUM* is assets under management, including risky assets and cash. *Income proxy* is the monthly average difference between high and low balances on checking accounts, *geo wealth proxy* is measured on a scale from 1 to 9 and indicates the average wealth level of individuals within a microgeographical area, and *I: main bank* is an indicator equal to one if a customer allocates at least half of the tax exemption limit to this bank. Reported values are calculated by first computing the annual average for the previous 12 months and then calculating the cross-sectional average of these values across all investors. Standard deviation is in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) All	(2) Non cryptocurrency	(3) Cryptocurrency investors	(4) T-test (3) - (2)
A. Demographic characteristics				
I: Male	0.75	0.75	0.90	0.15***
	(0.43)	(0.43)	(0.30)	(10.47)
Age	49.39	49.41	47.24	-2.17***
	(15.47)	(15.48)	(13.60)	(-4.26)
I: Academic title	0.06	0.06	0.05	-0.01
	(0.23)	(0.23)	(0.22)	(-0.90)
I: Joint account	0.14	0.14	0.14	0.00
	(0.34)	(0.34)	(0.35)	(0.40)
I: Main bank	0.36	0.36	0.48	0.12***
	(0.48)	(0.48)	(0.50)	(7.84)
Geo wealth proxy	6.05	6.05	6.02	-0.03
	(1.90)	(1.90)	(1.87)	(-0.47)
B. Wealth and income				
Total AUM (EUR)	49,761.11	49,514.92	80,341.21	30,826.29***
	(89,052.16)	(88,834.42)	(108,679.86)	(10.51)
Income proxy (EUR)	2,788.50	2,764.09	5,820.49	3,056.39***
	(12,847.45)	(12,161.50)	(47,844.81)	(7.22)
N	116,323	115,394	929	116,323

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Table 2: Portfolio characteristics

This table reports descriptive statistics on portfolio characteristics of cryptocurrency and noncryptocurrency investors from the full sample. The last column reports the difference in means between the groups. *Years with bank* defines the time from the start of the relationship until the end of 2017. *Risky share* is the portfolio value divided by total wealth. *Trade risk* is a measure provided by the bank on a scale from 0 (money market funds) to 5 (turbo certificates). Reported values are calculated by first computing the annual average for the previous 12 months and then calculating the cross-sectional average of these values across all investors. The variables *avg. cryptocurrency trade*, *avg. cryptocurrency holding,* and *avg. cryptocurrency share* are averaged over the holding period. Standard deviation is in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) All	(2) Noncryptocurrency	(3) Cryptocurrency investors	(4) T-test (3) - (2)
A. Investment experience				
Years with bank	12.28	12.30	11.01	-1.28***
	(5.42)	(5.42)	(6.06)	(-7.17)
Avg. monthly logins	27.08	26.64	82.53	55.89***
	(99.09)	(97.91)	(188.94)	(17.14)
Avg. monthly trades	2.03	1.97	9.04	7.07***
	(12.34)	(12.19)	(23.21)	(17.41)
I: Stock participation	0.70	0.70	0.95	0.26***
	(0.46)	(0.46)	(0.21)	(16.97)
I: Derivative participation	0.18	0.17	0.47	0.30***
	(0.38)	(0.38)	(0.50)	(24.08)
I: Warrant participation	0.04	0.04	0.17	0.13***
	(0.20)	(0.19)	(0.37)	(19.95)
I: Bond participation	0.07	0.07	0.08	0.01
	(0.26)	(0.26)	(0.27)	(1.10)

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B. Portfolio characteristics				
Portfolio value (EUR)	48,384.24	48,155.93	76,742.96	28,587.02***
	(187,148.62)	(187,260.04)	(170,481.15)	(4.64)
Avg. cryptocurrency trade	28.16	0.00	3,525.52	3,525.52***
	(803.89)	(0.00)	(8,286.20)	(144.61)
Avg. cryptocurrency holding	29.95	0.00	3,749.87	3,749.87***
	(1,442.72)	(0.00)	(15,714.26)	(81.10)
Avg. % of cryptocurrency	0.00	0.00	0.13	0.13***
	(0.02)	(0.00)	(0.22)	(196.63)
No. cryptocurrency holdings	0.02	0.00	2.43	2.43***
	(0.49)	(0.00)	(4.87)	(169.79)
Risky share	0.55	0.55	0.78	0.23
	(4.30)	(4.31)	(2.48)	(1.63)
Number of securities	6.92	6.85	15.05	8.19***
	(11.19)	(10.37)	(47.30)	(22.28)
Number of stocks	3.61	3.56	9.68	6.12***
	(8.81)	(7.84)	(45.41)	(21.11)
Number of funds	2.66	2.66	3.31	0.65***
	(4.52)	(4.50)	(6.13)	(4.37)
Share of stocks	0.49	0.49	0.62	0.13***
	(0.44)	(0.44)	(0.35)	(9.04)
Share of derivatives	0.04	0.04	0.08	0.04***
	(0.16)	(0.16)	(0.17)	(7.82)
Share of warrants	0.01	0.01	0.02	0.01***
	(0.08)	(0.08)	(0.10)	(3.77)
Share of bonds	0.02	0.02	0.01	-0.01*
	(0.12)	(0.12)	(0.07)	(-2.51)
Share of funds	0.43	0.43	0.26	-0.18***
	(0.43)	(0.43)	(0.31)	(-12.33)
Avg. trade risk	3.85	3.85	4.06	0.21***
	(0.48)	(0.48)	(0.31)	(13.10)
HHI	0.32	0.32	0.25	-0.07***
	(0.36)	(0.36)	(0.26)	(-5.60)
N	116,323	115,394	929	116,323

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Table 3: Return and diversification measures of investors

This table reports diversification and return measures for both cryptocurrency and noncryptocurrency investors. The table is based on the cryptocurrency investors in the sample, as well as a random sample of 1,000 noncryptocurrency investors at the end of December 2016. *Portfolio betas* are calculated following the method of Calvet, Campbell and Sodini (2007). *Annualized Return loss* is the average return lost by choosing the portfolio, rather than a combination of the benchmark portfolio with cash to achieve the same risk level. *Relative Sharpe ratio loss* compares the Sharpe ratio of an investor's portfolio to the Sharpe ratio of the benchmark. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels.

	(1) Noncryptocurrency investors	(2) Cryptocurrency investors	(3) T-test (2) - (1)
Portfolio beta	1.24	1.34	0.10**
	(0.57)	(0.72)	(2.81)
Annualized Return loss (%)	4.03	6.80	2.77
	(0.94)	(3.34)	(1.71)
Relative Sharpe Ratio Loss (RSRL)	0.28	0.31	0.03**
	(0.23)	(0.23)	(2.66)
N	726	611	1,337

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Table 4: Determinants of cryptocurrency investment

This table reports the odd ratios of crypto investors as the dependent variable in logit regressions. In Column (1), we report the results with demographic control variables, and in Column (2), we also control for wealth variables. Geographic fixed effects are based on the two-digit ZIP code level. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels.

	(1) Cryptocurrency Investor	(2) Cryptocurrency Investor
I: Male	3.088***	2.459***
	(0.354)	(0.284)
Age	1.058***	1.037**
	(0.013)	(0.013)
Age (squared)	0.999***	0.999***
	(0.000)	(0.000)
I: Academic title	0.832	0.668*
	(0.129)	(0.107)
I: Joint account	0.966	0.908
	(0.094)	(0.091)
I: Main bank	1.601***	1.134
	(0.111)	(0.082)
Years with bank	0.947***	0.935***
	(0.006)	(0.006)
Geo wealth proxy		0.943**
		(0.021)
Log. deposits (EUR)		1.018
		(0.009)
Log. income proxy (EUR)		1.032***
		(0.010)
Log. portfolio value (EUR		1.306***
		(0.028)
Number of securities		1.007***
		(0.002)
Avg. trade risk		4.302***
		(0.416)
Risky share		1.002
		(0.003)
Avg. monthly trades		1.012***
		(0.002)
Geo fixed effects	Yes	Yes
Pseudo R^2	3%	10%
N	100,053	100,053

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Table 5: Technology / product innovation and cryptocurrency investment

This table reports the odds ratios of investment in cryptocurrencies based on previous experience of technology usage and product innovation. For cryptocurrency investors, the dependent variables are from before the cryptocurrency investment. The dependent variable in Columns (1) and (2) indicates usage of a bank-owned mobile trading app as well as mobile banking. The dependent variable in Columns (3) and (4) indicates usage of a bank-owned robo-advisor that suggests a portfolio based on risk preferences and investment horizon. The dependent variable in Columns (5) and (6) indicates investment in any of the 20 largest precious metals ETFs before 2010. The pump and dump securities for Columns (7) and (8) are provided by Leutz et al. (2018). Columns (2), (4), (6) and (8) include additional control variables. Geographic fixed effects are based on the two-digit ZIP code level. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Technology innovation				Product innovation			
	Mobile Banking or Trading App user		Robo advisor user		Early commodity investor		Penny stock investor	
Cryptocurrency investor	5.527***	2.962***	1.346**	0.899	2.078***	1.478**	2.934***	2.714***
	(0.413)	(0.235)	(0.164)	(0.112)	(0.363)	(0.270)	(0.229)	(0.237)
Geo wealth proxy		0.979***		0.975***		1.035***		0.975***
		(0.008)		(0.008)		(0.015)		(0.007)
Log. deposits (EUR)		1.013***		1.078***		1.030***		0.994**
		(0.003)		(0.004)		(0.006)		(0.003)
Log. income proxy (EUR)		1.063***		1.065***		1.007		0.994**
		(0.004)		(0.004)		(0.006)		(0.003)
Log. portfolio value (EUR		1.223***		1.396***		1.418***		0.940***
		(0.008)		(0.011)		(0.022)		(0.005)
Avg. trade risk		4.805***		0.850***		1.171***		1.696***
		(0.178)		(0.012)		(0.049)		(0.039)
Geo fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	1%	13%	0%	10%	1%	13%	1%	14%
N	100,053	100,053	100,053	100,053	100,053	100,053	100,053	100,053

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Table 6: High risk sectors and markets

This table reports the usage of ETFs from high-risk sectors and markets. The last column reports the differences in means between the groups. Standard deviation is in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1) All	(2) Noncryptocurrency investors	(3) Cryptocurrency investors	(4) T-test (3) - (2)
Emerging market ETF investor	0.05	0.05	0.09	0.04***
	(0.21)	(0.21)	(0.29)	(6.22)
Solar sector ETF investor	0.07	0.06	0.17	0.11***
	(0.25)	(0.25)	(0.38)	(12.73)
Biotech sector ETF investor	0.07	0.07	0.25	0.18***
	(0.26)	(0.26)	(0.43)	(20.19)
N	100,053	99,181	872	100,053

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Table 7: Investment bias behavior and cryptocurrency investment

This table reports the odds ratios of investment in cryptocurrencies based on the propensity to show investment biases in pervious trades prior to 2016. The dependent variable, *High trend chasing preference,* is an indicator equal to 1 if the average preference for trend chasing is greater than or equal to the 75th percentile before investors invested in cryptocurrencies. *High lottery stock preference* is an indicator equal to 1 if the average preference for lottery-stocks is greater than or equal to the 75th percentile. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
	High trend chasing preference		High lottery stock preference	
Cryptocurrency investor	3.553***	2.808***	2.330***	2.248***
	(0.243)	(0.198)	(0.159)	(0.159)
Geo wealth proxy		1.004		1.006
		(0.005)		(0.004)
Log. deposits (EUR)		1.026***		1.059***
		(0.002)		(0.002)
Log. income proxy (EUR)		0.999		0.961***
		(0.002)		(0.002)
Log. portfolio value (EUR)		1.239***		0.978***
		(0.005)		(0.003)
Geo fixed effects	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes
Pseudo R^2	0%	6%	0%	5%
N	100,053	100,053	100,053	100,053

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Table 8: Trading and investment behavior and cryptocurrency investment

This table reports the correlation between cryptocurrency investment and investment behavior. The dependent variables across the table are the average monthly logins, monthly trades, and the number of securities held in the portfolio. Columns (2), (4) and (6) add additional control variables. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Avg. monthly logins		Avg. monthly trades		Number of securities	
Cryptocurrency investor	54.495***	45.625***	7.148***	6.578***	7.989***	5.330***
	(3.954)	(4.293)	(0.757)	(0.765)	(1.429)	(1.390)
I: Male		11.751***		0.679***		1.121***
		(0.756)		(0.029)		(0.062)
Age		-0.197*		0.011*		0.091***
		(0.090)		(0.004)		(0.007)
Age (squared)		-0.000		-0.000*		-0.001***
		(0.001)		(0.000)		(0.000)
I: Academic title		-1.778		0.125		0.478
		(1.496)		(0.129)		(0.256)
I: Joint account		20.523***		-0.038		0.188
		(1.515)		(0.044)		(0.108)
I: Main bank		5.620***		0.407***		1.052***
		(0.505)		(0.043)		(0.067)
Geo wealth proxy		0.001		-0.010		-0.036
		(0.130)		(0.009)		(0.026)
Log. deposits (EUR)		-0.645***		-0.057***		-0.114***
		(0.119)		(0.011)		(0.013)
Log. income proxy (EUR)		3.517***		0.061***		0.097***
		(0.061)		(0.004)		(0.011)
Log. portfolio value (EUR		2.382***		0.362***		2.193***
		(0.128)		(0.007)		(0.038)
Geo fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0%	4%	1%	3%	1%	21%
N	100,053	100,053	100,053	100,053	100,053	100,053

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Table 9: Single differences: trading and investment behavior around cryptocurrency adoption

This table reports the effect of cryptocurrency investments on investment behavior. The sample consists of cryptocurrency investors only. We control for demographic fixed effects, such as *gender, age, academic titles, joint accounts* and *main bank*, and individual fixed effects, such as *geo wealth proxy* and *the Log total wealth*. All specifications also include individual, month, and year fixed effects. Panel A includes cryptocurrency securities, and Panel B excludes them. Standard errors are in parentheses. ***, **, * indicate coefficients that are significant at the 1%, 5%, and 10% levels.

Panel A: Including cryptocurrencies

	(1) Average logins	(2) Average number of trades	(3) Number of securities
After cryptocurrency investment	16.49***	0.35	2.42***
	(2.724)	(0.40)	(0.29)
Individual fixed effects	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R2	61%	53%	95%
N	38,291	38,291	38,291

Panel B: Excluding cryptocurrencies

	(1) Average logins	(2) Average number of trades	(3) Number of securities
After crypto investment	16.49***	-0.24	2.04***
	(2.724)	(0.40)	(0.29)
Individual fixed effects	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R2	61%	53%	95%
N	38,291	38,291	38,291

Figures

Figure 1: Quarterly price development of Bitcoin

This figure shows the quarterly development of the Bitcoin price from 2013 to 2018 in US dollars.

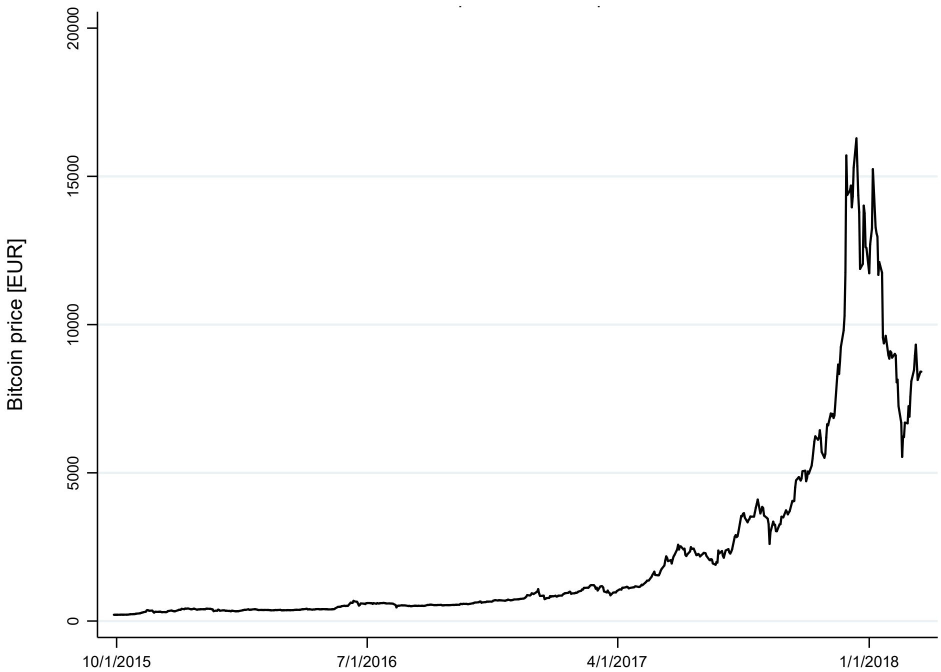

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Figure 2: Development of number of cryptocurrency investors and cryptocurrency holding value

This figure shows the development of the number of cryptocurrency investors in the sample (bars) and the portfolio holding value of cryptocurrency ISINs in the sample in EUR '000 (dashed line). The numbers are the reported numbers for the month and are not cumulative

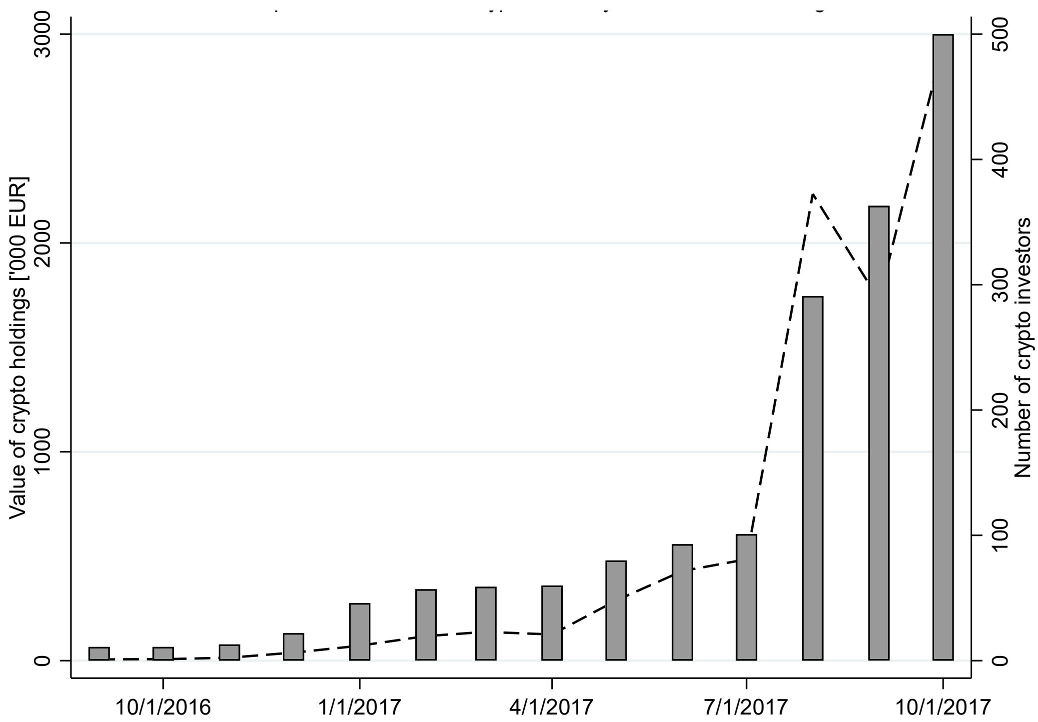

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Figure 3: Correlation between Bitcoin prices and selected indirect cryptocurrency investments

This figure shows the correlation of the Bitcoin price and the most widely held indirect investment vehicles in the sample. The selected ISINs are the most widely held ISINs in the sample and cover approximately 82% of all holdings. The price of the Bitcoin Tracker XBT and the Bitcoin Group SE share has been multiplied by 20 for improved scaling.

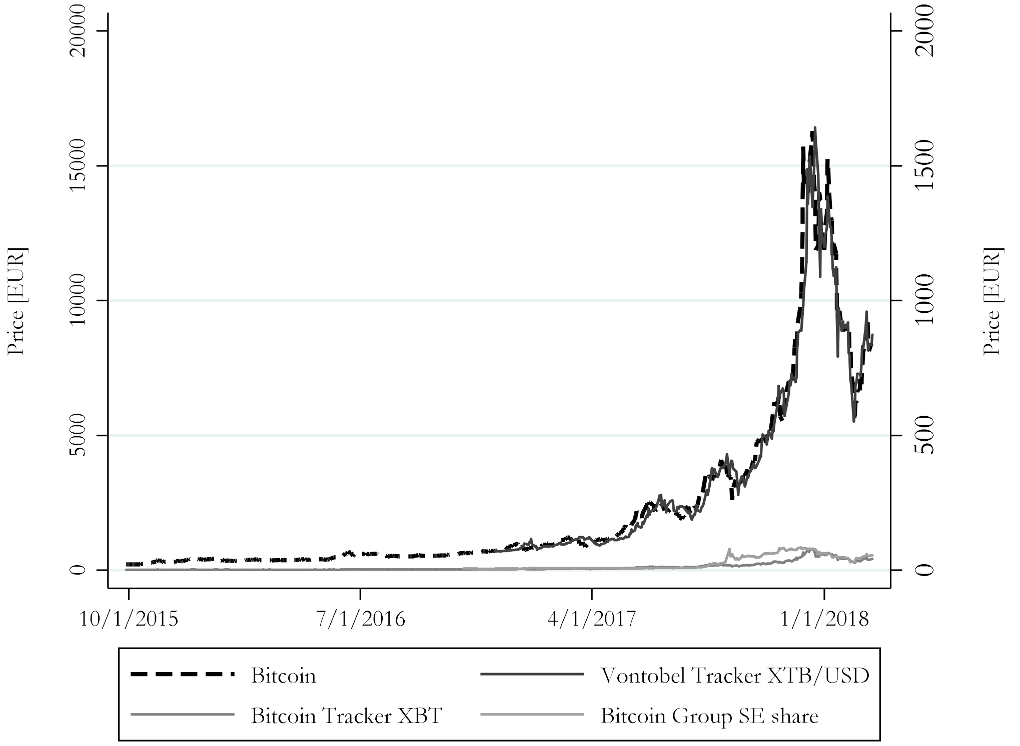

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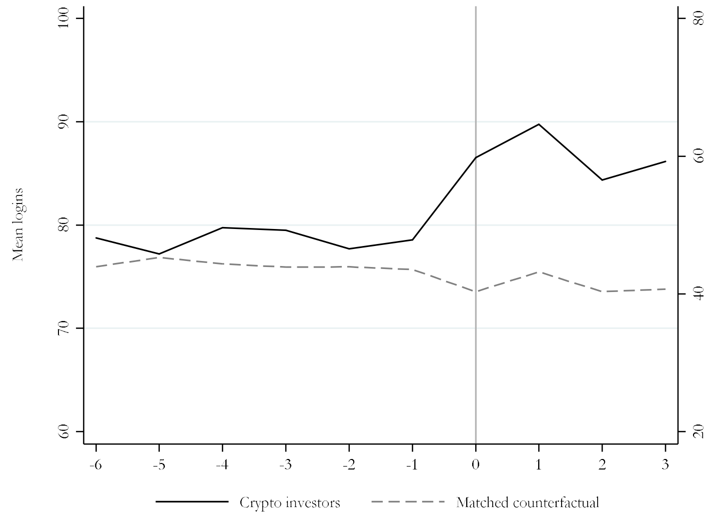
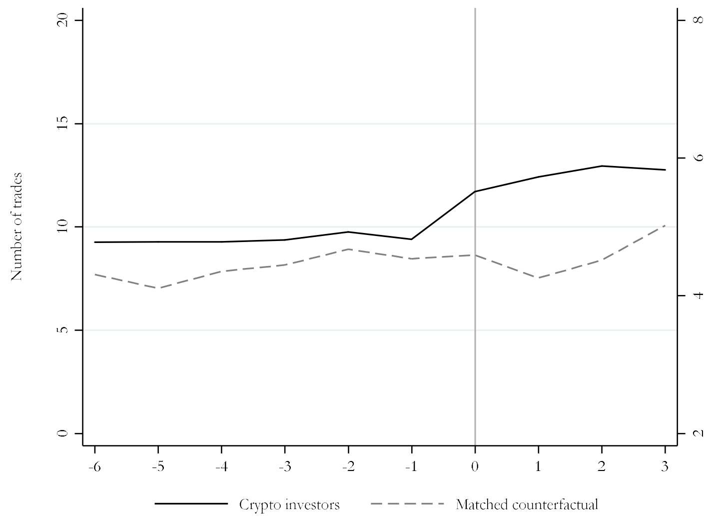
Figure 4: Investment behavior around cryptocurrency adoption

The following figures shows development of the *average monthly logins*, *number of securities* and *average number of trades* pre- and post-cryptocurrency investment for both the cryptocurrency investors and a matched counterfactual group (second axis). The x-axis states the month since initial cryptocurrency investment.

Panel A: Average monthly logins



Panel B: Average number of trades



Panel C: Average number of securities

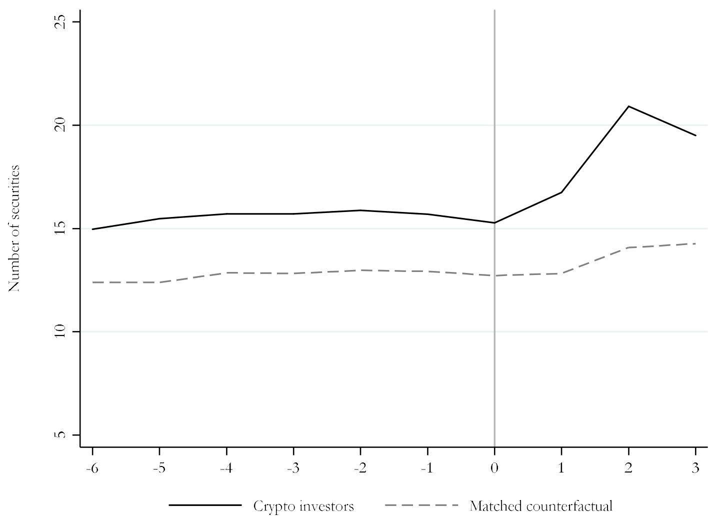


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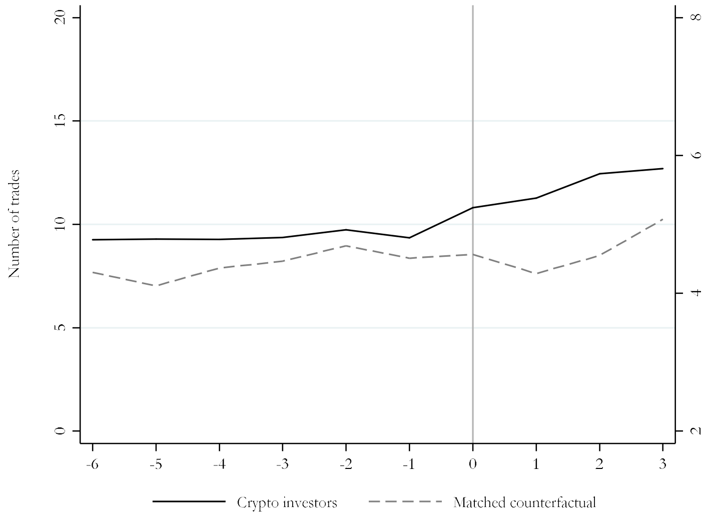
Figure 5: Investment behavior around cryptocurrency adoption without cryptocurrency securities

The following figures show the development of the *number of securities* and *average number of trades* pre- and post-cryptocurrency investment for both the cryptocurrency investors and a matched counterfactual group (second axis) without cryptocurrencies. The x-axis states the month since initial cryptocurrency investment.

Panel A: Average number of trades



Panel B: Average number of securities

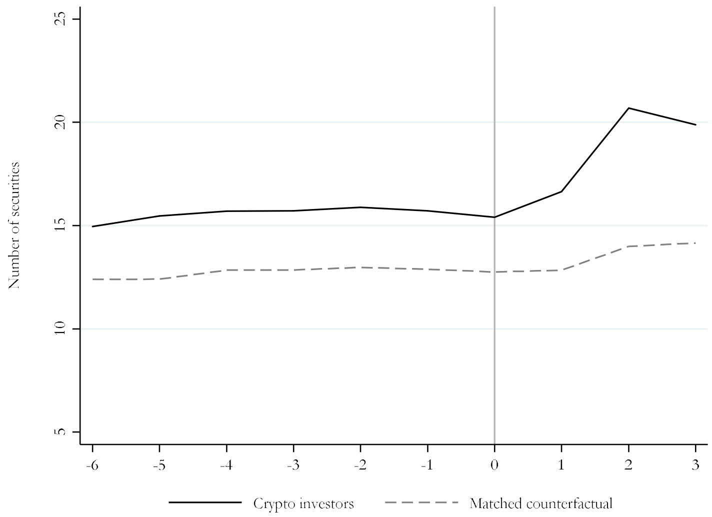
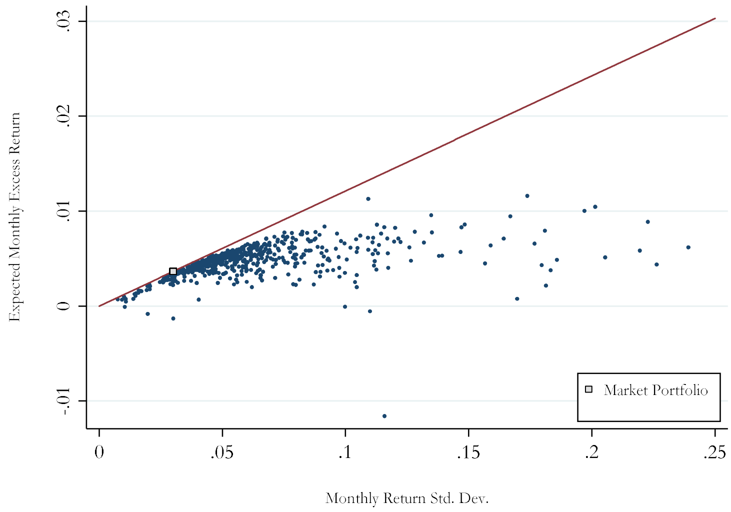


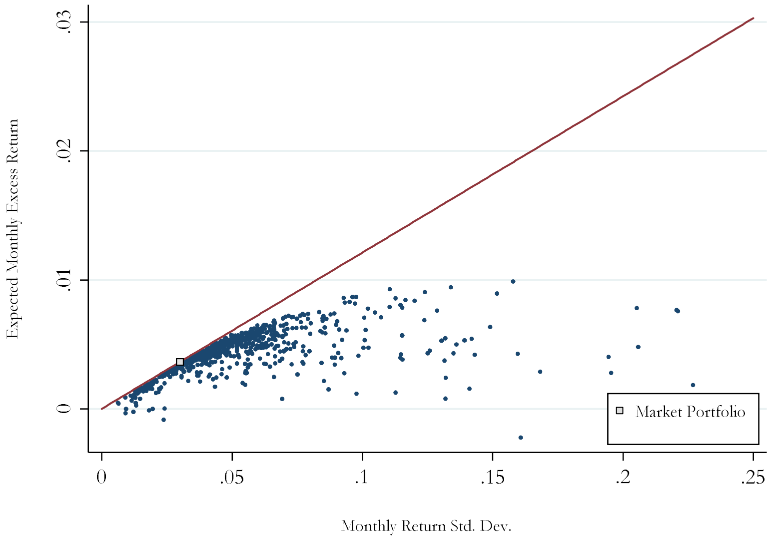
Figure 6: Mean-variance characteristics of investor portfolios

The following figures show the mean-variance characteristics of investors' portfolios for both cryptocurrency (first figure) and noncryptocurrency investors (second figure).The mean excess returns are inferred from a global CAPM using the methodology of Calvet, Campbell and Sodini (2007) and a market portfolio based on Jacobs, Müller and Weber (2014). The graphs are based on the cryptocurrency investors in the sample as well as a random sample of 1,000 noncryptocurrency investors at the end of December 2016.

Panel A: Cryptocurrency investors



Panel B: Non-Cryptocurrency investors



Appendix

Table 10: Overview of cryptocurrency securities

This table reports the 31 crypto-related securities and the characteristics used for the analysis in the paper.

ISIN	Name	Type	Management Fee
CA31932X1050	First Bitcoin Capital Corp. Registered Shares o.N.	Share	N/A
US05581M1071	BTCS Inc. Registered Shares DL -,001	Share	N/A
US09173J1007	Bitcoin Shop Inc. Registered Shares DL -,001	Share	N/A
US09173Y1073	Bitcoin Services Inc. Registered Shares DL -,01	Share	N/A
US05581M2061	BTCS Inc. Registered Shares DL -,001	Share	N/A
DE000A1TNV91	Bitcoin Group SE Inhaber-Aktien o.N.	Share	N/A
SE0007126024	XBT Provider AB O.E. 15(unl.) Bitcoin	Exchange Traded Note	2.50%
SE0007525332	XBT Provider AB O.E. 15(unl.) Bitcoin	Exchange Traded Note	2.50%
SE0010296574	XBT Provider AB O.E. 17(unl.) Ethereum	Exchange Traded Note	Not available
SE0010296582	XBT Provider AB O.E. 17(unl.) Ethereum	Exchange Traded Note	2.50%
CH0327606114	Bank Vontobel AG VONCERT 23.07.18 DL/Bitcoin	Certificate – Tracker	Not available
CH0374279666	Bank Vontobel AG VONCERT 23.07.18 DL/BitcoinC	Certificate – Tracker	Not available
DE000VL3TBC7	Vontobel Financial Products O.End Part.Z17(18/unl.) Index	Certificate – Tracker	1.50%
DE000VN5MJG9	Vontobel Financial Products Partizip. ZT 23.07.18 CrossRat	Certificate – Tracker	1.50%
DE000TR0Y9Q7	HSBC Trinkaus & Burkhardt AG TurboC O.End Bitcoin	Certificate – Knock out (Call)	Not available
DE000LS9KZ51	Lang & Schwarz AG O.End 17(17/unl.) WF02100000	Certificate – Index / Participation	0.95%
DE000LS9GNS7	Lang & Schwarz AG O.End 15(15/unl.) WF0BTCRSNG	Certificate – Index / Participation	0.95%
DE000LS9L251	Lang & Schwarz AG O.End 17(17/unl.) WF1BITCOIN	Certificate – Index / Participation	0.95%
DE000LS9L8X6	Lang & Schwarz AG O.End 17(17/unl.) WFBITCOIN1	Certificate – Index / Participation	0.95%
DE000LS22SH5	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 30	Certificate – Knock out (Call)	Not available
DE000LS22SK9	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 40	Certificate – Knock out (Call)	Not available
DE000LS22XK9	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 45	Certificate – Knock out (Call)	Not available
DE000LS22XL7	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 50	Certificate – Knock out (Call)	Not available
DE000LS22ZK4	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 25	Certificate – Knock out (Call)	Not available
DE000LS231S9	Lang & Schwarz AG TurboC 14.12.17 Bitcoin 47	Certificate – Knock out (Call)	Not available
DE000LS23RA0	Lang & Schwarz AG TurboC O.End Bitcoin 35,1247	Certificate – Index / Participation	Not available
DE000LS23RC6	Lang & Schwarz AG TurboC O.End Bitcoin 42,1505	Certificate – Index / Participation	Not available
DE000LS23RD4	Lang & Schwarz AG TurboC O.End Bitcoin 45,0629	Certificate – Index / Participation	Not available
DE000LS25CN0	Lang & Schwarz AG TurboC 12.06.18 Bitcoin 46	Certificate – Index / Participation	Not available
DE000LS25EA3	Lang & Schwarz AG TurboC O.End Bitcoin 38,1151	Certificate – Index / Participation	Not available
DE000LS25N27	Lang & Schwarz AG TurboC O.End Bitcoin 51,1172	Certificate – Index / Participation	Not available

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