Payment Firms, Cryptocurrencies, and CBDCs

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Abstract

We provide a method to identify and classify payment firms and assess the effect of two innovations – cryptocurrencies and central bank digital currencies (CBDCs) – on the payment industry. We find that payment firms' stock returns are uncorrelated with proxies for the rise and fall of cryptocurrencies, while payment firms' stock returns react significantly and negatively to central bank announcements on the introduction of CBDCs. Our results are consistent with the narrative that cryptocurrencies are a speculative asset class rather than a means of payment. In contrast, the market regards CBDCs as a potential threat to payment firms' business model.

Keywords: Payment firms, cryptocurrencies, stablecoins, central bank digital currencies

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1. Introduction

The rise of payment firms constitutes one of the most significant changes to the financial industry over the last decade. At the end of 2020, the combined market capitalization of all payment firms was more than USD 1.6 trillion, almost at par with the combined market capitalization of all commercial banks in the U.S. (USD 1.7 trillion). This is in stark contrast to just ten years earlier, when payment firms accounted for only one-fifth of the combined market capitalization of all commercial banks. Payment behavior has changed significantly over the past decade, with a decline in the use of cash and checks[1], an increase in digital payments, and various innovations that aim to upend the way we pay. In this paper, we (i) classify payment firms and document the rise of payment firms over the past decade, (ii) assess the effect of two types of innovations on the payment industry: cryptocurrencies and central bank digital currencies (CBDCs).

To document the rise of payment firms, we start by providing a method to identify and classify payment firms. To the best of our knowledge, no such classification has been done hitherto in the existing literature. Any study that aims to assess the effect of interventions on the payment industry – such as new regulations, technological innovation, or the introduction of CBDCs – needs to have a proper classification of payment firms. Standard industry codes currently assign payment firms to various industries, ranging from financial services to information technology, e-commerce, and even manufacturing ("calculating and accounting machines").[2] We develop a method to classify firms as payment firms based on a combination of a firm's SIC code and keywords in the business description. Our classification method lines up well with industry reports on the payment sector that typically rely on a subjective common-sense classification to define payment firms. Our approach

[1] See, for example, ECB (2022).

[2] Visa, for example, is classified as a depository institution under the Standard Industrial Classification System (SIC code 6099), it is classified as an Information Technology firm using the GICS system, and it is part of the S&P 500 Information Technology Sector Index. PayPal is either classified as an information technology firm (SIC and GICS), a financial sector firm (Morningstar), or as part of the e-commerce sector (Dow Jones Internet Commerce Index). Cantaloupe, a firm providing cashless payment terminals for vending machines, is classified under the SIC code 3578 ("Computer and Office Equipment / Calculating and Accounting Machines").

is also simple to use because SIC codes and business descriptions are widely available for companies across the world.

Following this classification, we document three key descriptive facts about the U.S. payment industry. First, at its height in 2020, the payment industry accounted for approximately 29% of the finance sector market capitalization. This was only marginally smaller than the share of commercial banks (30%) and larger than the share of insurance companies (22%), and other financial firms such as brokers, dealers, and non-depository institutions (19%). The share of the payment industry has steadily increased from 5% in 2000 to 9% in 2010 to 29% in 2020. In 2021, it receded to 22%; however, even the 2021 figure constitutes a more than fourfold increase relative to the year 2000. Second, payment firms are more profitable than other financial sector firms (Return on Assets of 5.3% in 2021 compared to 1.3% for other financial sector firms). Third, payment firms have grown much faster than the rest of the financial sector over the last decade (annual revenue growth of 8.8% versus 4.5%, respectively between 2010 and 2020). These descriptive facts are consistent with the existence of significant rents in the payment industry and growth driven by the trend towards non-cash payments.

Next, we assess the effect of two types of innovations on the payment industry, one aimed at replacing the existing payment infrastructure as we know it (cryptocurrencies) and the other one driven by central banks (CBDCs).

Two narratives accompany the rise in cryptocurrencies. The first narrative emphasizes the payment functionality. The original intention of Bitcoin was to be a peer-to-peer payment system that dispenses with the need for a (costly) intermediary. The second narrative emphasizes the investment motive. Cryptocurrencies created a novel asset class that has been widely adopted by both retail and institutional investors (Auer et al., 2022). We find no correlation between payment firms' stock returns and proxies for the rise and fall of cryptocurrencies. This no-result holds (i) for price and volume-based performance measures of Bitcoin and other cryptocurrencies, (ii) for transaction volumes of stablecoins, that is, cryptocurrencies that attempt to peg their values to a conventional currency[3], and (iii) in an event study design that uses the May-2022 crash of two of the major stablecoins. Our results suggest that neither Bitcoin nor other cryptocurrencies or stablecoins are seen as a direct competitive threat to payment firms. These results are consistent with the common narrative that cryptocurrencies are predominantly viewed as an asset class, not as a means of payment. It is also consistent with the notion that although stablecoins play a dominant role for transactions in the crypto universe they have a limited footprint beyond. Our findings reinforce the results from Makarov and Schoar (2022), who show that most of the transaction volume on the Bitcoin blockchain relates to speculative trading activity rather than payment activity. Our event study is forward looking, so our tests encompass not just the historical usage of crypto for payment but also the expectations of it being used for this purpose in the future.

In the next step, we assess the impact of central bank digital currencies (CBDCs) on payment firms. CBDCs are digital liabilities of central banks that are widely available to the general public. To date, CBDCs have not yet been launched in the United States or Europe, the two major economic regions where the payment firms in our sample generate most of their revenues. While we are not aware of any empirical study that analyzes the effects of CBDCs on payment firms, prior literature has pointed out the potential of CBDCs to reduce transaction costs of digital payments, rendering some intermediaries in the payment process redundant (Raskin and Yermack, 2018; Ahnert et al., 2022). If this were true, CBDCs could reduce the rents earned in the payment industry.

We leverage central bank communication to assess the impact of CBDCs on payment firms. Central banks have regularly released communication outlining their stance towards the introduction

[3] Stablecoins have seen tremendous growth in the past years, with the President's Working Group, the FDIC, and the OCC arguing that "If well-designed and appropriately regulated, stablecoins could support faster, more efficient, and more inclusive payments options."

of CBDCs over the 2016 to 2022 period. We rely on a database maintained by the Bank of International Settlement (BIS) to obtain an independent assessment of the sentiment of this central bank communication (Auer, Cornelli, and Frost, 2020). When central bank communication on CBDCs carries a positive stance, our index of payment firms declines by 44 basis points in a two-day window around the date on which the communication took place. Across all communication events, this adds up to a 19% loss in payment firms' market capitalization. Reassuringly, we only find significant event study returns for speeches held by Presidents and Vice-Presidents, and not for speeches held by less-senior central bank representatives.

We provide two placebo tests. First, we carry out event studies of central bank communication that cover the topic of CBDCs but have a neutral stance on the introduction of CBDCs. Reassuringly, we find a closely estimated zero announcement return for these events. This suggests it is not the topic of the speech, but indeed the central bank's stance that matters. Second, Central Bank Communication on CBDCs might be accompanied by other communication relating to the outlook of the economy, the condition of the financial sector, or regulatory actions more generally. We therefore provide a placebo test using financial firms' returns on days of positive-stance central bank communication on CBDCs. Reassuringly, we do not find any significant announcement effect. Taken together, our results suggest that CBDCs are seen as a potential threat to the profitability of payment firms' business model.

A significant part of the payments literature has focused on payments as one of the prime examples of two-sided markets and analyzed competition and pricing issues, the adoption and use of cash vis-à-vis other payment types, the regulation of fees that banks earn from payment transactions, or on household finance related topics on the use of credit cards.[4] In contrast, our paper

[4] For a discussion of pricing in two-sided markets, see Baxter (1983), Katz (2001), Rochet and Tirole (2002), Rochet and Tirole (2003), Shy and Wang (2011). For the adoption of payment types, see Quinn and Roberds (2008), Koulayev et al. (2016), Alvarez and Argente (2022). For the use of contactless payment methods, see Agarwal et al. (2019), Bounie and Camara (2020), Garratt and Van Oordt (2021), and Brown, Hentschel, Mettler, and Stix (2022). For the regulation of payment fees, in particular interchange fees, see Agarwal et al. (2015), Jambulapati and Stavins

analyzes the effect of two innovations, cryptocurrencies and CBDCs, on payment firms' business models.

A more recent strand of the literature has analyzed the competition of FinTech payment firms with traditional banks. Parlour, Rajan, and Zhu (2022) develop a model where FinTech payment providers disrupt informational flows to traditional banks and thus affect traditional banks' lending business. Ghosh, Vallee, and Zeng (2022) empirically document the informational synergies between cashless payments and lending. While these papers analyze the interplay between payment firms and traditional financial intermediaries, we focus on the effect of cryptocurrencies and CBDCs on payment firms.

We also contribute to the nascent discussion on cryptocurrencies and stablecoins.[5] Several papers investigate the use of Bitcoin and other cryptocurrencies as an investment class.[6] Catalini, Gortari, and Shah (2022) and Arner, Auer, and Frost (2020) provide an overview on the economics of stablecoins and their regulatory implications. Several other papers analyze the mechanisms in place to keep stablecoins stable as well as their actual stability in practice. Foley, Karlsen, and Putniņš (2019) document that close to half of all Bitcoin transactions involve illegal activity. Makarov and Schoar (2022) show that Bitcoin is rarely used for speculation, but rarely for transactions. Gorton and Zhang (2022) argue that stablecoins – a form of privately produced money – are generally not an effective medium of exchange because they are not always accepted at par and subject to runs. Our results suggest that cryptocurrencies and stablecoins are not regarded as a potential threat to payment firms' business model, while CBDCs are seen as a potential threat. These findings support the Gorton and Zhang (2022) view.

(2014), or Kay, Manuszak, and Vojtech (2018). For the use of credit cards by households see Ausubel (1991), Calem and Mester (1995), Gross and Souleles (2002), Meier and Sprenger (2010), Telyukova (2013), Liberman (2016), Stango and Zinman (2016), Ponce, Seira, and Zamarripa (2017).

[5] Stablecoins are a subcategory of cryptocurrencies. We use the term "cryptocurrencies and stablecoins" to highlight that our results also hold when only analyzing the interplay between stablecoins and payment firms.

[6] See, for example, Briere, Oosterlinck, and Szafarz (2015), Baur, Hong, and Lee (2018), Auer et al. (2022) and Hackethal et al. (2022).

Finally, our research is also related to the literature on CBDCs. The existing literature is largely theoretical in nature due to the fact that no major economy has introduced a CBDC on a larger scale so far. Existing papers focus on monetary policy (Barrdear and Kumhof, 2016; Brunnermeier, James, and Landau, 2019), financial stability (Barrdear and Kumhof, 2016; Brunnermeier and Niepelt, 2019; Fernández-Villaverde et al., 2021), and effects on commercial banks (Andolfatto, 2021; Fernández-Villaverde et al., 2021; Keister and Sanches, 2023, Williamson, 2022.). Our work is most intimately related to the subset of studies addressing the adaption of CBDCs (Khiaonarong and Humphrey, 2019; Garratt and Van Oordt, 2021; Li, 2023; Ahnert, Hoffmann, and Monnet, 2022; Ahnert et al., 2022). These studies point to transaction cost reductions and the potential redundancy of some financial intermediaries. To the best of our knowledge, we are first to empirically analyze how a possible introduction of CBDCs affects the valuation of payment firms.

2. Classification of Payment Firms and Descriptive Statistics

2.1 Classification of Payment Firms

Our data set ranges from 1990 to 2021. All variables are from *Compustat*. We cover listed firms located in the U.S. with SIC codes starting with '60' (*Commercial Banks*), '61/62' (*Brokers, Dealers, Non-Depositary Institutions*[7]), '63/64' (*Insurance*), and *Payment Firms*.[8] We define *Payment Firms* via the following two criteria:

[7] Non-depository institutions (SIC code starting with '61') could also form a separate category. Examples of non-depositary institutions include Fannie Mae, Freddie Mac, Ally Financial (formerly GMAC), as well as Rocket Companies, Lending Tree, and Lending Club. As of 2020, the combined market capitalization of all non-depository institutions was less than 3% of the finance sector market capitalization and we, therefore, subsume non-depository institutions under one category together with brokers and dealers.

[8] The definition of commercial banks via SIC code '60' follows Gandhi and Lustig (2015). We make two manual adjustments to the SIC-code based firm classifications. First, we classify Citigroup (SIC code '6199') as commercial bank. Second, we classify Coinbase (SIC code '6099') as non-depository institution. Note that Gandhi and Lustig use header SIC code data (from *CRSP*) while we rely on historical SIC code data (from *Compustat*). Using header SIC codes instead of historical SIC codes does not make a material difference as the two-digit SIC codes rarely vary over time. One difference between CRSP and Compustat is that bank holding companies are sometimes classified with a SIC code starting with 67 in CRSP, while Compustat classifies bank holding companies that are mainly commercial banks with a SIC code starting with 60.

(i) the *Compustat* business description contains at least one of the words ‘payment’ or ‘merchant solution’, and

(ii) the SIC code is ‘6099’ (*Functions related to Depository Banking*; examples: Visa, Mastercard), ‘6141’ (*Personal Credit Institutions*; examples: American Express[9], Discover), or does not start with ‘6’.

The latter condition ensures we are not picking up financial firms for which payment services constitute only one of many business lines, but only pure play payment firms[10]. We cross-check our definition with industry reports from Nilson, the key provider of statistics on the payment industry. We find that our definition has a 96% overlap with the subjective common-sense definition used in these industry reports.[11] As of 2021, our definition yields 42 payment firms. Out of these 42 payment firms, 28 firms have a SIC code starting with ‘73’ (*Business Services*; examples: PayPal, Block/Square), 6 firms have the SIC code ‘6099’ (*Functions related to Depository Banking*, examples: Visa, Mastercard), 4 firms have the SIC code ‘6141’ (*Personal Credit Institutions*; example: Discover), and 4 firms have other SIC codes. The aggregate market capitalization of payment firms is concentrated in SIC code ‘6099’ (53%), SIC codes starting with ‘73’ (35%), and SIC code ‘6141’ (12%). The remaining SIC codes account for less than 1% of the total value.[12]

We further classify payment firms into three subcategories:

(i) *Payer-facing* payment firms, that is, firms that enable consumers to make payments. Examples include credit card-issuing banks as well as services such as Apple or Google Pay. These firms authenticate the identity of a particular consumer, verify that the

[9] Before 2010, the SIC code for American Express was either ‘6199’ (*Finance Services*) or ‘6211’ (*Security Brokers, Dealers, and Flotation Companies*). We manually classify American Express as payment firm throughout the entire sample period.
[10] A few originally pure-play payment firms such as PayPal have started offering non-payment-related services over time. We continue to classify these firms as payment firms since the respective activities represent only a minor fraction of these firms’ total revenues.
[11] Nilson reports a list of publicly listed payments firms in its reports since 2021. In 2020, our definition of payment firms results in a payment sector market capitalization of USD 1.647 trillion, while the definition from Nilson results in a payment sector market capitalization of USD 1.690 trillion, of which USD 1.630 trillion are overlapping with our definition.
[12] We compute market capitalization based on *Compustat* using end-of-calendar-year values for the share price (*prcc_c*) multiplied by shares outstanding (*csho*).

consumer has sufficient funds available, and settle transactions in the consumer's bank account.

(ii) *Payee-facing* payment firms, that is, firms that enable merchants to receive payments. Examples include Fiserv, PayPal[13], Square/Block, or Global Payments. These firms provide payment terminals (in-store), payment gateways (online), and processing services.

(iii) *Credit Card Networks*, that is, firms that set the rules and standards for the payment infrastructure but typically do not have a direct client relationship with consumers or merchants. Examples include Visa and Mastercard.[14]

Appendix A provides a detailed overview of the companies involved in (retail) payment transactions.[15]

Our data has two principal limitations. First, it does not cover payer-facing payment firms, such as card-issuing banks and technology firms like Apple. These entities derive a portion of their market capitalization from payment-related services, but we are unable to isolate this component. Second, we only focus on pure-play payment firms and disregard, for example, traditional banks (which commonly provide various services throughout the payment value chain). Consequently, our estimate of the size of the payment sector represents only a lower bound. Moreover, the data limitations imply that the following analyses rely exclusively on payee-facing firms and networks but do not consider payer-facing entities.[16]

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[13] PayPal has an interface to the payer (merchant) as well as the payee (consumer) but is typically classified as payee-facing. The reason is that PayPal fully replaces the payee-facing firms in the payment value chain; however, PayPal still relies on the services provided by both networks and issuing banks.

[14] The business models of American Express and Discover differ from Visa and Mastercard as they act both as card networks but also directly issue credit cards to consumers, that is, they combine functions (i) and (ii).

[15] Note that regulation that governs the design of credit card contracts or limits credit card fees typically applies to payer-facing firms. For example, the Durbin Amendment in the U.S. or the EU cap on credit and debit interchange fees do not regulate the fees that credit card networks can earn, nor do they regulate the fees that merchants pay.

[16] Note there are two possible ways to include payer-facing firms: first, U.S. banks report quarterly income from interchange fees. These reports can be used to assess a lower limit of the importance of payment services for card-issuing banks. Second, American Express and Discover act both as card networks but also directly issue credit cards to consumers. Absent other contaminating factors, any difference in the stock returns of American Express/Discover vis-à-vis Visa/Mastercard can thus be attributed to the payer-facing part of their payment business model.

2.2 Descriptive Statistics

2.2.1 Size and Growth of the Payment Sector

Figure 1 plots the finance sector market capitalization by subsector over time. In 1990, banks (36%) and insurance companies (46%) made up the lion's share of the finance sector market capitalization, followed by brokers, dealers, and non-depository institutions (12%) and payment firms (6%). In 2020 in turn, payment firms accounted for approximately 29% of the finance sector market capitalization, almost at par with commercial banks (30%) and exceeding the value of all other subsectors.[17] Although payment firms' share of the finance sector market capitalization receded back to 22% in 2021, this figure still constitutes a more than fourfold increase relative to the beginning of the twenty-first century. Between 2005 and 2020 alone, payment firms' market capitalization increased from USD 140 billion to USD 1,647 billion.

Figure 2 illustrates that the observed rise of payment firms is not simply the result of a composition effect (i.e., new listings in the payment subsector) but mainly driven by a return effect (i.e., an increase in market capitalizations of existing payment firms). Between 1990 and 2021, a value-weighted index of payment firm stocks would have grown by a factor of 61, significantly outperforming banks (19), insurances (29), and brokers, dealers, and non-depository institutions (41).

Table 1 presents the largest firms by market capitalization in each of the four finance subsectors as of 2021. Remarkably, three of the most valuable financial firms in the United States were payment firms (Visa, USD 459 billion; Mastercard, USD 352 billion; PayPal, USD 220

[17] For the end of 2020, our data set contains 40 payment firms, 109 insurance companies, 122 brokers, dealers, and non-depository institutions, as well as 517 banks. Thus, payment firms also have the highest market capitalization per firm across all finance subsectors.

billion), with only two banks (J.P. Morgan, USD 466 billion; Bank of America, USD 359 billion) and one insurance company (United Health, USD 473 billion) remaining in the top six.

2.2.2 Economic Performance of the Payment Sector

Table 2 provides key financial statistics that further substantiate the rise of payment firms over the past decade. We highlight two characteristics that are consistent with the observed surge in payment firms' market capitalizations. First, relative to other players in the financial industry, such as commercial banks, payment firms are highly profitable. For example, the average annual return on assets in the payment subsector over the 2010s was 4.5%, more than four times higher than the profitability of other financial subsectors (commercial banks: 0.9%, brokers, dealers, and non-depository institutions: 0.7%, insurance companies: 1.2%). Second, the payment sector has experienced significant real economic growth. Total revenues in the payment sector increased from USD 86 billion in 2010 to USD 217 billion in 2021 (+151.9%). On an annual basis, average value-weighted revenues of payment firms have grown by 8.8% over the 2010s, relative to just 1.6% growth in the commercial banking sector[18].

Overall, the statistics are consistent with the existence of substantial rents in the payment sector and the broader narrative that the shift towards digital payments has resulted in a notable expansion of the payment industry. Simultaneously, Table 2 suggests that payment firms have unique characteristics that set them apart from other players in the financial sector, underlining the need for a distinct classification.

[18] For banks, revenues are defined as "total current operating revenue and net pretax profit or loss on securities sold or redeemed" (*Compustat*).

3. Payment Firms and the Rise (and Fall) of Cryptocurrencies

3.1. The Rise (and Fall) of Cryptocurrencies

Cryptocurrencies constitute one of the major innovations in the financial system over the last decade. The Bitcoin White Paper was published in 2008 and implemented in January 2009. At the end of 2021, the universe of cryptocurrencies consisted of more than 8,000 cryptocurrencies with a combined market capitalization of USD 2.2 trillion.[19] Stablecoins – cryptocurrencies that are pegged to a conventional currency – provide liquidity and payment services in the crypto universe. In 2021, the average daily transaction volume of the four major stablecoins was USD 102 billion. As points of reference, the market capitalization of all payment firms at the end of 2021 was USD 1.6 trillion, and the transaction volume of the four major card networks was USD 55 billion per day on average in 2021.

Two narratives accompany the rise in cryptocurrencies. The first narrative emphasizes the payment functionality. Bitcoin was originally designed as a peer-to-peer electronic cash system that allows payments to be made without an intermediary, and the e-commerce use case features prominently in the Bitcoin White Paper.[20] Some prominent business leaders have embraced the payment functionality narrative and several major companies have experimented with accepting Bitcoin payments for their products.[21]

The second narrative emphasizes the investment narrative. Cryptocurrencies created a novel asset class, and the emergence of ETFs and related derivatives paved the way for broader investor engagement, including both retail and institutional adoption (Auer et al., 2022). For a given

[19] The market capitalization of cryptocurrencies was more than USD 3trn in November 2021, before falling below USD 1trn in June 2022.
[20] The title of the Bitcoin White Paper is "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008). The abstract of the Bitcoin White Paper states that Bitcoin would allow "payments to be sent directly from one party to another without going through a financial institution" and the first sentence in the introduction directly addresses the e-commerce use case: "Commerce on the Internet has come to rely almost exclusively on financial institutions serving as trusted third parties to process electronic payments."
[21] Bitcoin is accepted in the Microsoft Xbox Store, other prominent cases include Overstock, Home Depot, Starbucks, AT&T, and Whole Food. Tesla announced plans to accept Bitcoin in 2021. In 2014, Bill Gates told Bloomberg "Bitcoin is better than currency in that you don't have to be physically in the same place and, of course, for large transactions, currency can get pretty inconvenient." (https://www.bloomberg.com/news/videos/2014-10-02/bill-gates-bitcoin-is-exciting-because-its-cheap). Elon Musk stated in 2021 "There is a good chance that crypto is the future currency of the world."

cryptocurrency the payments narrative and the investment narrative should be mutually exclusive in the long run: a means of payment requires stability of value, while the investment case emphasizes the possibility to generate sizeable returns. In the short term, a rise in the use of currency for payment and liquidity services might well coincide with a sharp appreciation in the currencies' value.[22] It is also possible that the appeal of some cryptocurrencies stems from their use for investment purposes, while the popularity of others stems from a means-of-payment functionality.

Based on the intentions spelled out in the Bitcoin White Paper, one might hypothesize that a successful private cryptocurrency jeopardizes the position of established payment firms because it allows payments to be made without an intermediary. We test this hypothesis in two ways: First, we use prices of cryptocurrencies as a proxy for the success of cryptocurrencies and examine whether the prices of cryptocurrencies correlate with payment firms' stock prices. Second, we analyze whether the rise and fall of stablecoins are correlated with payment firms' stock prices.

3.2. Payment Firms and Cryptocurrencies (Excluding Stablecoins)

Assume there is new information $\eta_i \in \{\text{positive, negative}\}$ about the expected adoption of cryptocurrencies. If cryptocurrencies exist to replace traditional payment intermediaries, then positive information about the expected adoption of cryptocurrencies would constitute negative information for traditional payment intermediaries (and vice versa). We would therefore expect stock prices of traditional payment intermediaries to react negatively to new information that updates the beliefs of the expected adoption of cryptocurrencies (and vice versa). If, on the other hand, cryptocurrencies are merely used for investment purposes, then any new information on

[22] See, for example, Fratzscher (2009) for the drivers of global exchange rates during the global financial crisis. The need for U.S. dollars by non-U.S. firms for payment and liquidity services was one of the contributing factors to the appreciation of the U.S. dollar vis-à-vis other currencies.

cryptocurrency adoption is not necessarily correlated with stock prices of traditional payment intermediaries.

There are two ways to test this conjecture. First, we can specifically look at a particular piece of new information η_i about the expected adoption of cryptocurrencies and test for the stock price reaction of traditional intermediaries in an event study setting. Second, we can look at conditional correlations between performance indicators of cryptocurrencies and stock prices of traditional payment intermediaries, while controlling for common factors that are generally known to explain stock prices. The latter approach has the advantage that it does not require to specify specific news events that update beliefs about cryptocurrencies. We, therefore, start with this latter approach and discuss event study tests in section 3.3. In particular, we estimate a time series regression of the excess return of payment firms on the excess return of cryptocurrencies, controlling for the standard Fama-French three factors (Fama and French, 1992):

$$R_t - R_{Ft} = \alpha_i + \gamma(B_t - R_{Mt}) + b(R_{Mt} - R_{Ft}) + sSMB_t + hHML_t + e_t \qquad (1)$$

R_t are weekly returns of an index of payment firms. B_t are weekly cryptocurrency returns which we proxy using the *S&P Bitcoin Index* (available since 2014) in our baseline analysis. R_{Ft} is the risk-free rate, and $(R_{Mt} - R_{Ft})$, *SMB*, and *HML* are the factors from the Fama-French three-factor model. The coefficient γ captures the conditional sensitivity of payment firms' stock returns to cryptocurrency returns.

Our approach relies on two assumptions: First, we need to adequately control for common factors that jointly drive stock returns of traditional payment firms and returns of cryptocurrencies. The Fama-French three-factor model is a natural starting point, and we provide further robustness tests using other factor models below. Second, we need to assume that payment firms' stock returns are not directly affected by new information on cryptocurrencies beyond the payment-functionality competition channel. This could be violated if traditional payment firms hold cryptocurrencies or offer investment services into cryptocurrencies. In this case, a negative correlation between cryptocurrencies and traditional payment firms due to the competition channel might be blurred by payment firms' activities in the cryptocurrency sphere. We, therefore, provide robustness tests below in which we exclude those payment firms that are most exposed to cryptocurrency activities.

Panel A of Table 3 provides the results of Regression (1). Conditional on the three Fama-French factors, the return of payment firms is uncorrelated with the *S&P Bitcoin Index*. The coefficient of interest is -0.004 with a *t*-stat of -0.57 and a 95% confidence interval ranging from -0.02 to +0.01, that is, a narrow interval centered around zero (column 1). The results are robust to using the market model, the Fama-French five-factor model (Fama and French, 2015), or the Carhart four-factor model (Carhart, 1997) instead of the Fama-French three-factor model; they are also robust to using monthly instead of weekly returns (results are available on request). To address potential concerns that our findings could be specific to certain time periods (e.g., due to the infancy of the cryptocurrency market at the beginning of the sample period), we split our sample into two halves and rerun Regression (1) for two subperiods. Neither for the subperiod from 2014-2017 (column 2) nor the subperiod from 2018-2021 (column 3) do we find any significant correlations between payment firm returns and returns of the *S&P Bitcoin Index.* Bitcoin returns are only one of several proxies for the rise and fall of cryptocurrencies. However, column (4) of Table 3 shows that our findings are not specific to Bitcoin but also hold when regressing payment firm returns on a broader cryptocurrency index (the *S&P Cryptocurrency Broad Digital Markets Index*, available since 2017).

Panel B of Table 3 reports the results of additional robustness tests. As shown in columns (1) and (2), we do not find a significant sensitivity of payment firms' stock returns to the *S&P Bitcoin Index* when considering the two subtypes of payment firms (payee-facing payment firms and networks) in isolation. In column (3), we exclude those firms from the payment index that have themselves established cryptocurrency initiatives and whose stock returns could therefore be positively correlated with the returns of cryptocurrencies (contrary to the competition channel). This includes PayPal, and Block/Square, which both allow their users to execute cryptocurrency transactions. For the adjusted payment index, the regression coefficient of interest becomes slightly more negative relative to our baseline results (-0.010) but remains statistically insignificant (*t*-stat -1.33). Finally, in column (4), we consider the excess returns of an index that only consists of cryptocurrency-exposed firms (i.e., PayPal and Block/Square) as outcome variable. As to be expected, the coefficient of interest is now larger than in our baseline specification (0.023), but still economically small and statistically insignificant (*t*-stat 1.42)

Overall, our results do not provide any evidence that Bitcoin or other cryptocurrencies are viewed as competition to traditional payment firms. This no-result is extremely robust, holding for different proxies of cryptocurrency returns, for different sample periods, as well as for different subsectors of the payment industry.

3.3. Payment Firms and Stablecoins

Stablecoins are designed to keep a stable value vis-à-vis a reference currency, typically the U.S. Dollar. The four largest stablecoins (*Tether*, *USDCoin*, *TerraUSD*, and *BinanceUSD*) accounted for a combined transaction volume of USD 102 billion per day throughout 2021. This compares to a combined daily payment transaction volume of USD 55 billion for the four largest card networks (Visa, Mastercard, American Express, Discover). Stablecoin transaction volumes have thus become sizeable relative to transaction volumes by established payment firms. Stablecoins support a wide range of activities in crypto markets, but it is not clear whether stablecoins are viewed as a threat to traditional payment firms for transactions outside of the crypto universe.

Our aim is to test whether indicators of the rise and fall of stablecoins are correlated with payment firms' stock returns. If stablecoins are seen as a substitute for traditional payment firms' services, then an increased adoption of stablecoins should be negatively correlated with payment firms' stock returns and vice versa. We test this hypothesis in two separate analyses: a time-series regression as well as an event study of the May-2022 stablecoin crash.

3.3.1 Time Series Regressions

We test whether the adoption of stablecoins is correlated with payment firms' stock returns via the following regression:

$$R_t - R_{Ft} = \alpha_i + \gamma(Volume_t) + b(R_{Mt} - R_{Ft}) + sSMB_t + hHML_t + e_t \qquad (2)$$

As in Section 3.2, *Rt* are returns of an index of payment firms and we use weekly trading data. $Volume_t$ is the adjusted weekly log transaction volume of the four largest stablecoins (*Tether*, *USDCoin*, *TerraUSD*, *BinanceUSD*). We adjust the raw weekly logarithm of the transaction volume in two ways: First, we de-trend the log transaction volume over a 10-week period following Campbell, Grossmann, and Wang (1993) and Tetlock (2007). Econometrically, this accommodates the fact that trading volume is non-stationary. Economically, we aim to measure transaction volume relative to the past trend because any trend in transaction volumes might already be incorporated in payment firms' stock prices. Second, we normalize the resulting de-trended log transaction volume to a mean of zero and a standard deviation of one to facilitate the interpretability of the coefficients.

Panel A of Table 4 provides the results. The return of payment firms is uncorrelated with stablecoin transaction volume. The coefficient of interest is -0.0004 (a one standard deviation increase in detrended stablecoin transaction volume decreases payment firm stock returns by 0.04%) with a *t*-stat of -0.45 and a 95% confidence interval ranging from -0.0020 to +0.0012, that is, a narrow interval centered around zero. We find insignificant results across all four major stablecoins.

Results are also robust to using the market model, the Fama-French five-factor model (Fama and French, 2015) or the Carhart four-factor model (Carhart, 1997) instead of the Fama-French three-factor model. We also do not find a significant sensitivity of payment firms' stock return to stablecoin volumes in different subperiods, nor for any of the two subtypes of payment firms (payee-facing payment firms and networks), see Panel B of Table 4.

3.3.2 Event Study: the May-2022 Crash

In May 2022, two of the four biggest stablecoins lost their peg to the U.S. Dollar. On 8 May (Saturday), *TerraUSD* – the fourth largest stablecoin at that time – dropped to 0.985 USD before dropping to as low as 0.35 USD on 9 May (Sunday). On 11 May, *Tether* – the largest stablecoin – dropped to 0.9935 USD before dropping further to slightly below 0.95 USD on 12 May. Both events were unexpected, akin to a bank run, and in particular the break of *Tether*'s peg was widely reported in key media outlets.[23]

If stablecoins are seen as a competitive threat to traditional payment firms, then the May-2022 stablecoin crash should positively affect payment firms' stock returns. We separately conduct an event study analysis for both events. For the *TerraUSD* crash, we choose the event window from Friday, 6 May (closing price) to Monday, 9 May (closing price). For Tether, we choose the window from Tuesday, 10 May (closing price) to Thursday, 12 May (closing price). We determine event study returns using a market model with an estimation window ranging from 260 trading days prior to the event to 10 days prior to the event. Results are shown in Table 5. Across both events, payment firms' abnormal stock returns are very close to zero. For the *Terra* event, the abnormal event window return is insignificantly negative (-0.42%). For the Tether event the abnormal event window return is insignificantly positive (0.46%) We also do not find any significant abnormal returns when respectively considering the two subtypes of payment firms (payee-facing payment firms and networks) in isolation.

[23] See, for example, CNBC (12 May 2022): The world's biggest stablecoin has dropped below its $1 peg; Financial Times (12 May 2022): Crypto industry shaken as Tether's dollar peg snaps; Bloomberg (12 May 2022): Terra Was Too Big to Fail, and It Failed: Bloomberg Crypto

Taken together, our results do not provide any evidence that stablecoins are viewed as a substitute for the services provided by traditional payment firms. The rise and fall in stablecoins is uncorrelated with payment firms' stock returns. Overall, market participants do not seem to regard stablecoins as a potential threat for payment firms' business model.

4. Payment Firms and Central Bank Digital Currencies (CBDCs)

The prior section looked at whether privately produced digital money has the potential to substitute for existing services provided by payment firms. This section explores digital money produced by central banks – and accessible to the broader public – that is, central bank digital currencies (CBDCs). The majority of payment firms in our sample derive most of their revenues in the U.S. and the Eurozone. We, therefore, explore whether a (potential) introduction of a CBDC in the U.S. or in the Eurozone is seen as a threat to payment firms' business models.

Our empirical strategy is as follows: central banks regularly communicate their stances on important policy topics via speeches. Over the 2016 to 2022 period, central banks in the U.S. and the Eurozone have made various speeches outlining their stance toward the introduction of CBDCs. We rely on a database maintained by the Bank of International Settlements (BIS) that collects all central bank speeches (as well as other forms of communication) on CBDCs and assigns a sentiment score to each of these observations (Auer, Cornelli, and Frost, 2020). The sentiment of an observation can be +1 (communication with a positive stance towards the introduction of a CBDC), 0 (communication with a neutral stance towards the introduction of a CBDC), or -1 (communication with a negative stance towards the introduction of a CBDC). Figure 4 depicts a timeline of central bank communication by stance. In total, our data set includes 113 observations, of which 48 have a positive stance, 52 a neutral stance, and 13 a negative stance toward the introduction of a CBDC.

Communication is more frequent in the later years (2020 to 2022) and the sentiment towards CBDCs has gradually shifted towards a positive stance, both in the U.S. and in Europe.

We employ an event study approach to examine the stock market reaction of payment firms to central bank communication, conditioning on the sentiment of the communication. Specifically, we estimate the following regression:

$$R_t = \alpha + \mathrm{b}\, R_{Mt} + \tau_+ \, D_t^+ + \tau_+ \, D_t^- + \tau_0 \, D_t^0 + \varepsilon_t \qquad (3)$$

R_t is the daily return on the index of payment firms, R_{Mt} is the daily market return (value-weighted return of all *CRSP* firms, taken from Kenneth French's webpage), and D_t is a set of dummy variables equal to one in a two-day window around the communication date with a positive stance (+), a negative stance (-) or a neutral stance on CBDCs (0).[24] We provide specifications where we include each dummy variable (positive, negative, neutral) separately as well as specifications where all dummy variables are included simultaneously. We use robust standard errors throughout our specifications.[25] The sample period is from January 2016 to June 2022.

Table 6, Panel A presents the main results. The coefficients in column (1) refer to communication with a positive stance towards CBDCs. When central bank communication carries a positive stance towards CBDCs, the index of payment firm returns declines by 22 basis points (*t*-stat = -2.47), equivalent to 44 basis points over our two-day window around each event. Across all 48 observations, this adds up to a 19% loss in payment firms' market capitalization. When central bank communication carries a negative stance towards CBDCs, payment firm returns increase by 13 basis points (*t*-stat = 1.48, marginally insignificant at conventional significance levels). Note that the number of communication events with a negative sentiment is significantly lower than the

[24] As we only know the day but not the exact time when the central bank communication took place, we consider a two-day window around every communication event as our event window. For example, if some communication was released on 10 May, our dummy variable is equal to one for both 10 May and 11 May.

[25] Note that in a standard event study, the coefficient *b* and the standard deviation of abnormal returns would be determined in an estimation window before the event. Our regression specification uses the entire sample period and estimates one coefficient *b* for all events. In practice, differences are minimal, and we obtain similar results when estimating abnormal returns using a separate estimation window for each event.

number of communication events with a positive sentiment (13 versus 48 observations, respectively), limiting the statistical power of the test. Most of the communication with a negative sentiment also took place at the beginning of our sample period, where a negative stance towards CBDCs might not have been unexpected to market participants. As a placebo test, we also carry out event studies around central bank communication that addresses the topic of CBDCs but has a neutral stance on their introduction. Reassuringly, we find a closely estimated zero announcement return for these observations (see column (3) of Table 6).

Column (4) of Table 6 estimates all three dummies (positive, negative, and neutral stance) jointly. Results are extremely similar to the regressions that separately estimate each event type. Columns (5) and (6) split the results by region (Europe and U.S.). While the U.S. coefficient is higher (34 basis points for the U.S. versus 21 basis points for Europe for communication with a positive sentiment towards CBDCs), it is also noisier due to the lower number of U.S. observations.

Figure 3 illustrates the distribution of return residuals (using the market model) of an index of payment firms around events with central bank communication on CBDCs. The negative mean return on days with positive-sentiment communication is not driven by just a few outliers, but return residuals are generally skewed to the left, with a significantly larger share of return residuals falling in the [-3%, -1%] interval compared to days with negative-sentiment communication on CBDCs.

Table 6, Panel B reports the results of additional robustness tests. Columns (1) and (2) distinguish between the two subtypes of payment firms (payee-facing payment firms and networks). The general pattern remains unchanged: we observe negative coefficients for positive communication on CBDCs, positive coefficients for negative communication on CBDCs, and insignificant coefficients for neutral communication on CBDCs. Our findings further suggest that, among the two subtypes of payment firms, payee-facing entities react somewhat more to the possible introduction of a CBDC. Their returns decline by 28 basis points on days with positive communication on CBDCs (t-stat = -2.45), relative to a decline in card network returns of 19 basis points (t-stat = -1.71). In column (3), we only consider those observations in the BIS database that relate to speeches (as opposed to other forms of central bank communication)[26]. Results remain largely unchanged relative to the baseline specification. In columns (4) and (5), we split the sample based on speaker-seniority. We find that positive communication on CBDCs from representatives that serve as President or Vice President of their respective central banks has a significant negative effect on payment firm returns (coefficient = -0.0032, t-stat = -2.63). On the other hand, positive communication on CBDCs from less-senior central bank representatives does not have a significant effect (coefficient = -0.0013, t-stat = -1.10).

Central Bank Communication on CBDCs might be accompanied by other communication relating to the outlook of the economy, the condition of the financial sector, or regulatory actions more generally. Table 7, therefore, provides a placebo test using returns of financial firms (proxied by the S&P 500 sector index Financials) around days of Central Bank Communication on CBDCs. Reassuringly, we find that neither positive-stance nor negative-stance communication has any effect on financial firms in general. Payment firms are unique in their negative reaction to positive-sentiment speeches on CBDCs.

Taken together, our results suggest that payment firms' valuation is negatively affected by central bank communication with a positive stance towards CBDCs. This is consistent with the view that the market regards CBDCs as a potential threat to payment firms' business model. Our results thus suggest that central-bank-issued digital money (CBDCs) is perceived differently than privately produced digital money (cryptocurrencies). These results are in line with the Gorton and Zhang (2022) argument that privately produced money is not an effective medium of exchange, while

[26] In total, our sample includes 106 speeches, five interviews, one online blog article, and one newspaper op-ed. By focusing on speeches, we address possible concerns that the non-speech observations in the sample could add noise to the analysis.

CBDCs might increase the efficiency of payments, and thus harm the profits currently realized by payment firms.

5. Conclusion

In this paper, we introduce a systematic approach to classify firms as payment firms. Based on this approach, we document a significant rise of payment firms over the past decade. Next, we show that payment firms' stock returns are uncorrelated with proxies for the rise and fall of cryptocurrencies – consistent with the narrative that cryptocurrencies are predominantly viewed as an asset class, not as a means of payment. In contrast, we find that stocks of payment firms react negatively to central bank announcements with a positive stance towards the introduction of a central bank digital currency (CBDC). These results suggest that CBDCs are seen as a potential threat to the business model of payment firms.

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Figure 1: Share of Finance Market Capitalization by Finance Subsectors

This figure shows the market capitalization for subsectors of finance scaled by the total finance market cap in the U.S. (these shares sum up to exactly 100% for each year.) The data is based on U.S.-listed firms with a SIC code of '60' (*Commercial Banks*), '61/62' (*Brokers, Dealers, Non-Depositary Institutions*), '63/64' (*Insurance*), and *Payment Firms*. We define *Payment Firms* as all firms that simultaneously fulfill both of the following two criteria: i) SIC code of '6099' or '6141' or SIC codes that do not start with '6', and ii) the *Compustat* business description contains the word 'payment' or 'merchant solution'. The sample period is from 1990 to 2021. Market capitalization is taken from *Compustat* using end-of-calendar-year values for the share price (*prcc_c*) multiplied by shares outstanding (*csho*).

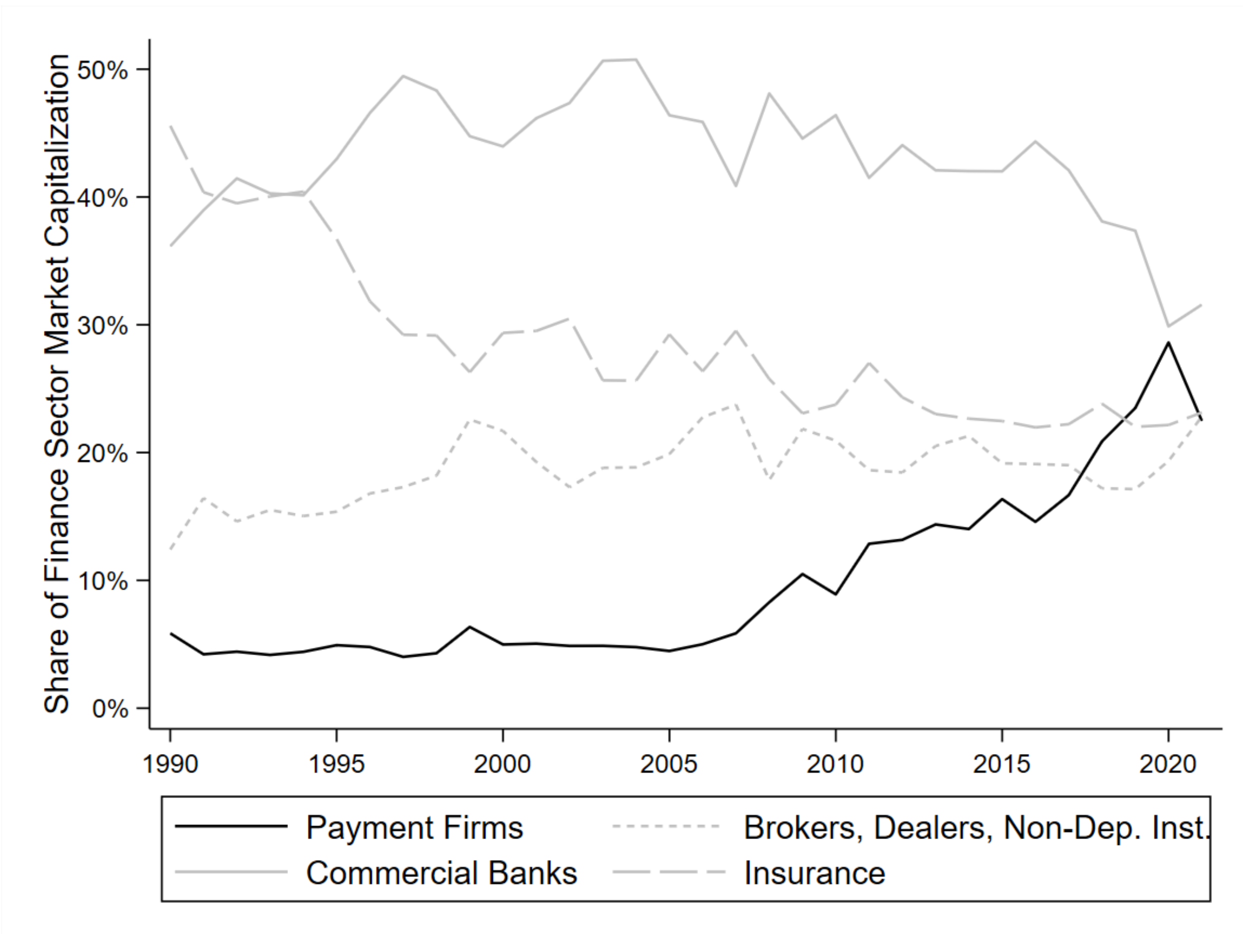


Figure 2: Cumulative Stock Returns Over Time by Finance Subsectors

This figure shows the cumulative returns for value-weighted indices of finance subsectors, indexed to 1 as of 01-Jan-1990. The data is based on U.S.-listed firms with a SIC code of '60' (*Commercial Banks*), '61/62' (*Brokers, Dealers, Non-Depositary Institutions*), '63/64' (*Insurance*), and *Payment Firms*. We define *Payment Firms* as all firms that simultaneously fulfill both of the following two criteria: i) SIC-code of '6099' or '6141' or SIC codes that do not start with '6', and ii) the *Compustat* business description contains the word 'payment' or 'merchant solution'. The sample period is from 1990 to 2021. Stock returns are monthly holding period returns (*ret*) from *CRSP*.

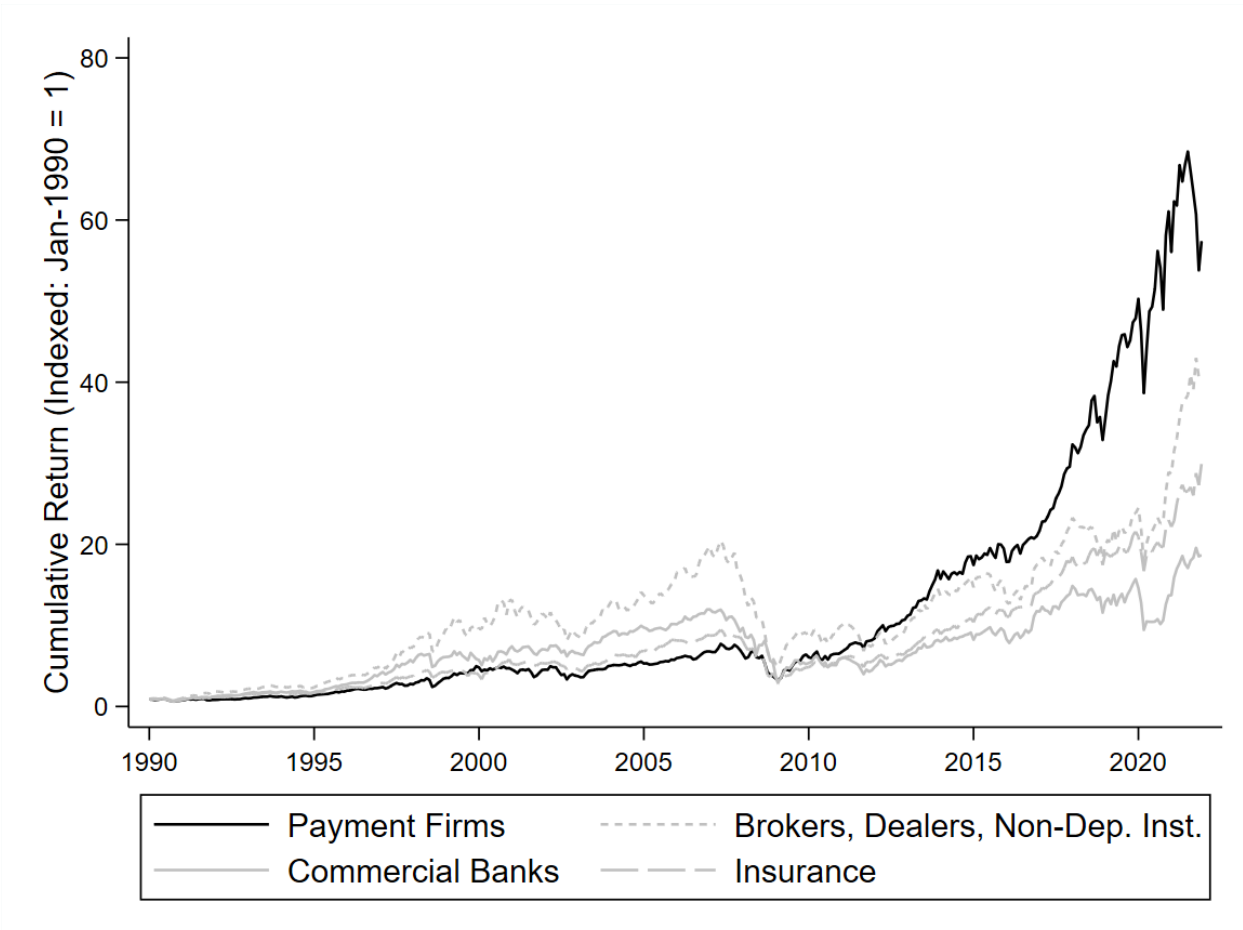
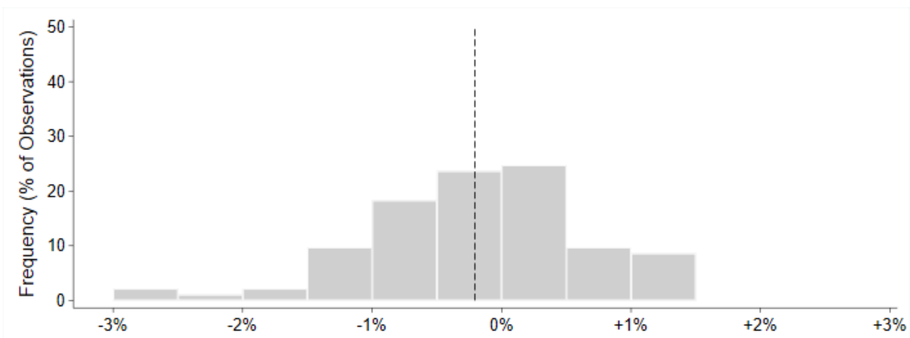


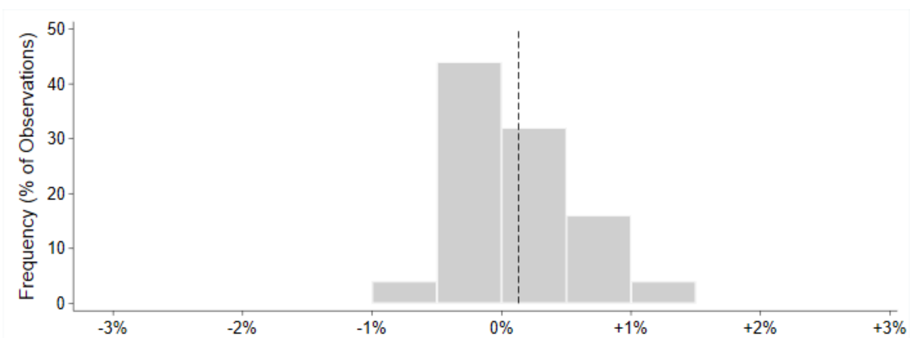
Figure 3: Payment Firm Return Residuals Around Days with Communication on CBDCs

This figure shows the distribution of return residuals of an index of payment firms around events with central bank communication on CBDCs. We rely on the BIS database from Auer, Cornelli, and Frost (2020) and define events as days on which there is communication on CBDCs from representatives of either the U.S. Federal Reserve, the ECB, or individual member countries of the Eurozone. The sample period is from January 2016 to June 2022. Event windows have a length of two days and include the trading day directly after an event day (as we do not know whether the communication happened before or after market closing). For the payment index, we use daily value-weighted returns of payment firms, where payment firms are defined via the SIC code and the business description, see Section 2.1. Return residuals are computed based on a market model and defined as the residuals in a linear regression of daily payment index returns on daily market returns (taken from Kenneth French's website). In Panel A, we consider events with positive sentiments towards CBDCs. In Panel B, we consider events with negative sentiments towards CBDCs. In Panel C, we consider events with neutral sentiments towards CBDCs. The dashed vertical lines indicate the respective mean return residuals.

Panel A: Positive Communication



Panel B: Negative Communication



Panel C: Neutral Communication

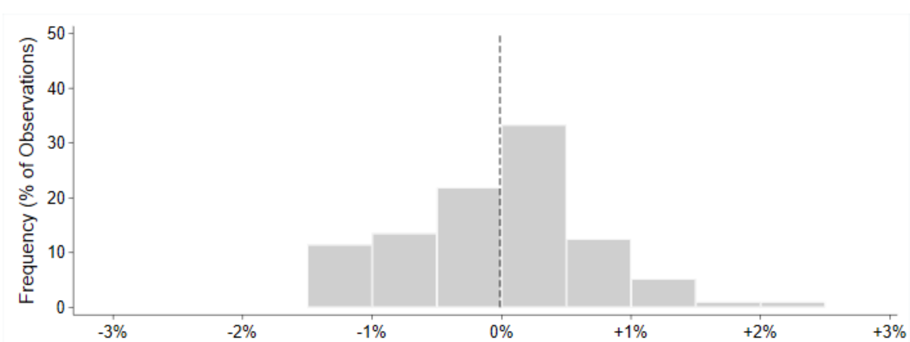


Figure 4: Timeline – Central Bank Communication on CBDCs

This figure illustrates the timeline of central bank communication on CBDCs based on Auer, Cornelli, and Frost (2020). It plots the sentiment (positive/negative/neutral) of each communication event against the day on which the communication took place. Euro events (navy circles) are defined as days on which there is communication on CBDCs from representatives of either the ECB or individual member countries of the Eurozone. U.S. events (red crosses) are defined as days on which there is communication on CBDCs from representatives of the U.S. Federal Reserve. The dashed lines represent the trends in communication sentiment over time by region. Trends are defined as the average sentiment of all communication events associated with a specific region that have been observed up to a specific day.

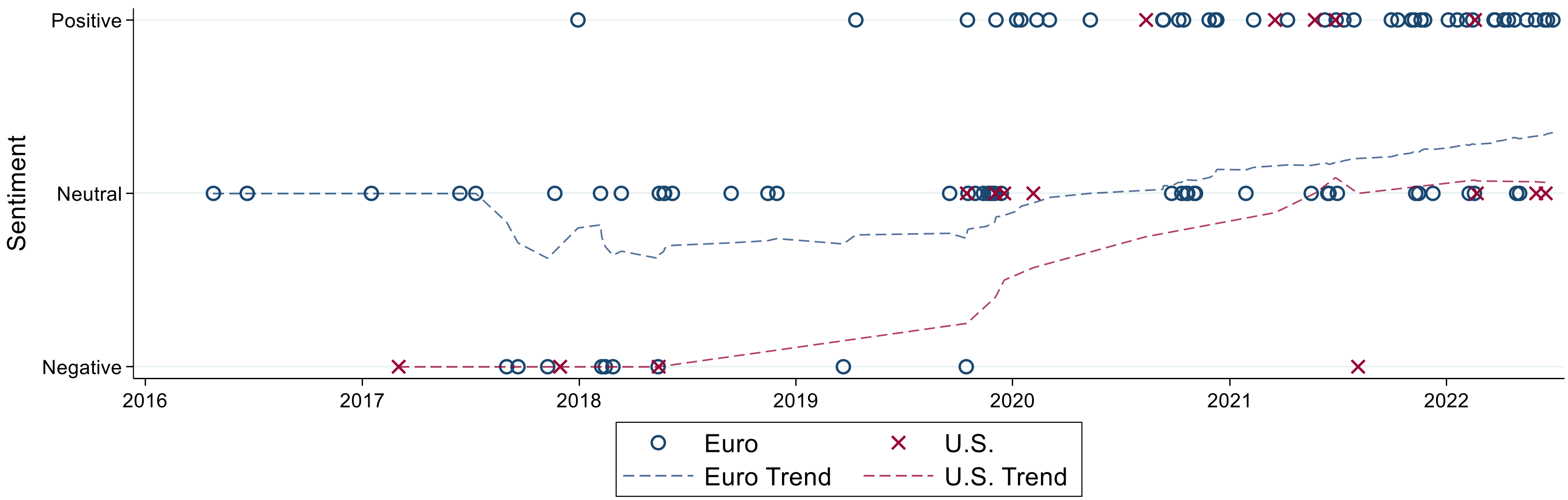


Table 1: Largest Firms by Subsector in 2021

This table provides a list of the ten largest firms by market capitalization at year-end 2021 for each of the four finance subsectors. The data is based on U.S.-listed firms in 2021 with SIC codes '60' (*Commercial Banks*), '61/62' (*Brokers, Dealers, Non-Depositary Institutions*), '63/64' (*Insurance*), and *Payment Firms* (see Section 2.1 for a detailed definition).

Rank	Payment Firms	Commercial Banks	Brokers, Dealers, Non-Deposit. Inst.	Insurance
1	Visa	JPMorgan Chase	Morgan Stanley	UnitedHealth
	$459bn	$466bn	$174bn	$473bn
2	Mastercard	Bank of America	Charles Schwab	Elevance Health/Anthem
	$352bn	$359bn	$159bn	$112bn
3	PayPal	Wells Fargo	BlackRock	Marsh & McLennan
	$220bn	$186bn	$139bn	$88bn
4	American Express	Citigroup	Goldman Sachs	Cigna
	$124bn	$120bn	$133bn	$74bn
5	Block/Square	PNC	Blackstone	Progressive Corp
	$75bn	$84bn	$91bn	$60bn
6	Fiserv	U.S. Bancorp	CME	Humana
	$67bn	$83bn	$82bn	$60bn
7	FIS	Truist	ICE	MetLife
	$66bn	$78bn	$77bn	$52bn
8	Global Payments	BNYM	Capital One	Centene
	$38bn	$47bn	$60bn	$48bn
9	Discover	SVB Financial	Coinbase	AIG
	$33bn	$40bn	$55bn	$47bn
10	Affirm	First Republic	MSCI	Prudential
	$27bn	$37bn	$51bn	$41bn

Table 2: Financial Statistics – Payments Firms vs. Banks

This table summarizes key financial metrics for payment firms and banks. The data is based on payment firms (see Section 2.1 for a detailed definition) and U.S.-listed firms with SIC code '60' (*Commercial Banks*). The sample period ranges from 2000 to 2021 and is split by decades. We aggregate the data across two dimensions: First, we aggregate the data on an annual level for payment firms and banks, respectively; next, we take simple averages across the annually aggregated data to compute decade-subsector-level summary statistics. *Firms* is the average number of firms. *Market Cap* is the average aggregate market capitalization (in USD million). *Equity* is the average aggregate book equity value (in USD million). *Assets* is average aggregate asset value (in USD million). *Revenue* is the average aggregate revenue (in USD million). *Net Income* is the average aggregate net income (in USD million). *ROA* is the average aggregate return on assets (in %). *ROE* is the average aggregate return on equity (in %). *Revenue Growth* is the aggregate value-weighted growth in revenues (in %).

	Payment Firms			**Commercial Banks**		
	2000s	**2010s**	**2020/21**	**2000s**	**2010s**	**2020/21**
Firms (#)	46	41	41	479	589	480
Size						
Market Cap ($m)	145,957	598,772	1,606,677	1,210,550	1,500,518	1,959,797
Assets ($m)	249,362	508,335	829,639	8,497,946	12,992,766	18,198,884
Equity ($m)	37,925	110,937	225,631	688,649	1,298,929	1,579,632
Revenue ($m)	62,337	133,310	200,744	604,403	643,196	677,937
Profitability						
Net Income ($m)	6,019	23,237	36,960	69,626	113,979	164,112
ROA (%)	2.38	4.54	4.44	0.90	0.86	0.89
ROE (%)	15.99	21.10	16.32	10.93	8.58	10.37
Growth						
Revenue Growth (%)	4.94	8.84	8.87	8.51	1.63	-5.11

Table 3: Payment Firm Stock Returns and Cryptocurrencies

This table depicts factor loadings for different variants of payment firm indices when regressed on different cryptocurrency indices across different sample periods. In Panel (A), the dependent variable is the weekly value-weighted excess return of payment firms (return in excess of the weekly rate that, over four weeks, compounds to the one-month U.S. Treasury bill rate from Ibbotson and Associates Inc.). Payment firms are defined via the SIC code and the business description (see Section 2.1). The factor loadings are determined in a Fama-French three-factor model, which is augmented using two different cryptocurrency indices (*Crypto*). In columns (1) to (3), *Crypto* is the abnormal return of the S&P Bitcoin Index (S&P BTC). In column (4), *Crypto* is the abnormal return of the S&P Cryptocurrency Broad Digital Market Index (S&P CBDM). Abnormal returns are defined as returns in excess of the market return (taken from Kenneth French's website). In column (1), the sample period is from Jan-2014 to Dec-2021. In column (2), the sample period is from Feb-2014 to Dec-2017. In column (3), the sample period is from Jan-2018 to Jan-2021. In column (4), the sample period is from Mar-2017 to Dec-2021. Panel (B) builds on the baseline analysis in column (1) of Panel (A) but uses different outcome variables. Columns (1) and (2) distinguish payment firms by 'Payee-Facing' firms (e.g., Fiserv, PayPal, Block/Square) and credit card 'Networks' (e.g., Visa, Mastercard). In column (3), the payment index excludes PayPal and Block/Square (i.e., firms that themselves engage in cryptocurrency activities). In column (4), the payment index only consists of PayPal and Block/Square. T-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Payment Sector Stock Returns (Full Sample) and Different Proxies for Cryptocurrency Returns

	(1)	**(2)**	**(3)**	**(4)**
	S&P BTC	**S&P BTC (2014-2017)**	**S&P BTC (2018-2021)**	**S&P CBDM**
Crypto	-0.004	0.003	-0.011	-0.013
	(-0.57)	(0.37)	(-0.96)	(-1.43)
Market	1.145***	1.052***	1.171***	1.170***
	(36.70)	(22.33)	(27.08)	(29.40)
SMB	-0.068	-0.046	-0.064	-0.065
	(-1.27)	(-0.70)	(-0.77)	(-0.89)
HML	-0.026	-0.094	-0.013	-0.029
	(-0.71)	(-1.54)	(-0.27)	(-0.63)
Constant	0.000	0.001	-0.000	0.000
	(0.25)	(0.69)	(-0.06)	(0.41)
Observations	418	209	209	253
Adjusted R^2	0.776	0.722	0.792	0.785

Panel B: Robustness Tests – Payment Sector Subcategories, Subsamples Without/With Inherent Crypto Exposure

	(1) S&P BTC (Payee-Facing)	(2) S&P BTC (Networks)	(3) S&P BTC (Ex. PayPal, Block/Square)	(4) S&P BTC (PayPal, Block/Square)
Crypto	0.003	-0.011	-0.010	0.023
	(0.39)	(-1.27)	(-1.33)	(1.42)
Market	1.182***	1.113***	1.098***	1.364***
	(35.08)	(29.18)	(32.40)	(19.00)
SMB	0.023	-0.129**	-0.101*	-0.000
	(0.39)	(-1.97)	(-1.73)	(-0.00)
HML	-0.264***	0.149***	0.130***	-0.675***
	(-6.59)	(3.29)	(3.23)	(-8.12)
Constant	-0.000	0.001	0.000	0.001
	(-0.22)	(0.69)	(0.34)	(0.71)
Observations	418	418	418	337
Adjusted R^2	0.760	0.695	0.737	0.550

Table 4: Stablecoins

This table depicts factor loadings for an index of payment firms. The dependent variable is the weekly value-weighted excess return of payment firms (return in excess of the weekly rate that, over four weeks, compounds to the one-month U.S. Treasury bill rate from Ibbotson and Associates Inc.). Payment firms are defined via the SIC code and the business description (see Section 2.1). Factor loadings are determined in a Fama-French three-factor model, which is augmented using the weekly log transaction volume of stablecoins, detrended over a 10-week period and standardized to a mean of zero and a standard deviation of one. In Panel (A) column (1), stablecoin transaction volume is defined as the aggregate transaction volume across *Tether*, *USD Coin*, *Terra*, and *Binance*. Columns (2) to (5) depict results when considering the individual transaction volumes of the respective stablecoins in isolation. The sample period is from May-2015 to Jun-2022, all returns are weekly returns. Panel (B) reports the results of different robustness tests, defining stablecoin transaction volume as the aggregate transaction volume across *Tether*, *USD Coin*, *Terra*, and *Binance*. Columns (1) and (2) split the sample into two subperiods (May-2015 to December-2018 and Jan-2019 to Jun-2022, respectively). Columns (3) and (4) distinguish payment firms by 'Payee-Facing' firms (e.g., Fiserv, PayPal, Block/Square) and credit card 'Networks' (e.g., Visa, Mastercard). T-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Payment Sector Stock Returns and Stablecoin Transaction Volume

	(1) **Stablecoins**	**(2)** **Tether**	**(3)** **USD Coin**	**(4)** **Terra**	**(5)** **Binance**
Detrended Standardized Log(Trading Volume)	-0.0004	-0.0004	-0.0014	0.0016	0.0007
	(-0.45)	(-0.49)	(-0.91)	(0.55)	(0.37)
Market	1.1371***	1.1373***	1.1621***	1.0711***	1.1883***
	(33.51)	(33.51)	(21.98)	(8.49)	(18.93)
SMB	-0.0794	-0.0794	-0.0709	0.1147	-0.0119
	(-1.28)	(-1.28)	(-0.71)	(0.59)	(-0.10)
HML	-0.0343	-0.0343	0.0014	-0.0164	0.0342
	(-0.88)	(-0.88)	(0.03)	(-0.14)	(0.54)
Constant	0.0004	0.0004	-0.0008	-0.0019	-0.0018
	(0.52)	(0.52)	(-0.52)	(-0.61)	(-0.94)
Observations	373	373	184	73	135
Adjusted R^2	0.7583	0.7583	0.7516	0.5339	0.7533

Panel B: Robustness Tests – Sample Subperiods and Payment Sector Subcategories

	(1) May'15 - Dec'18	(2) Jan'19 - Jun'22	(3) Payee-Facing	(4) Networks
Detrended Standardized Log(Trading Volume)	-0.0001	0.0015	-0.0004	-0.0003
	(-0.22)	(0.42)	(-0.43)	(-0.28)
Market	1.0568***	1.1728***	1.1919***	1.1021***
	(28.82)	(22.12)	(30.55)	(27.25)
SMB	-0.0982	-0.0780	0.0161	-0.1503**
	(-1.63)	(-0.78)	(0.23)	(-2.04)
HML	-0.2200***	-0.0000	-0.2763***	0.1382***
	(-4.02)	(-0.00)	(-6.18)	(2.98)
Constant	0.0015**	-0.0015	-0.0006	0.0011
	(2.16)	(-0.70)	(-0.59)	(1.12)
Observations	191	182	373	373
Adjusted R^2	0.8236	0.7421	0.7297	0.6775

Table 5: Event Study – Crypto Crash in May 2022

This table depicts the results of two event studies. Panel A presents the results of the Terra crash from May 6 to May 9, when *TerraUSD* lost its peg to the USD. Panel B presents the results of the Tether crash from May 10 - May 12, when *Tether* (temporarily) lost its peg to the USD. Column (1) reports results for all payment firms. Columns (2) and (3) distinguish payment firms by 'Payee-Facing' firms (e.g., Fiserv, PayPal, Block/Square) and credit card 'Networks' (e.g., Visa, Mastercard). The first row in each table shows raw returns, the second row shows the return of the market (taken from Kenneth French's webpage), and the third row shows the abnormal return using the market model. T-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Terra Crash (May 6 Closing - May 9 Closing = Friday Closing - Monday Closing)

	(1) All Payment Firms	(2) Payee-Facing	(3) Networks
Return	-4.77%	-4.54%	-4.88%
Market Return	-3.54%	-3.54%	-3.54%
Abnormal Return Using Market Model	-0.42%	0.78%	-1.10%
	(-0.36)	(0.45)	(-0.80)

Panel B: Tether Crash (May 10 Closing - May 12 Closing = Wednesday Closing - Thursday Closing)

	(1) All Payment Firms	(2) Payee-Facing	(3) Networks
Return	-1.86%	-2.97%	-1.29%
Market Return	-1.78%	-1.78%	-1.78%
Abnormal Return Using Market Model	0.46%	0.04%	0.61%
	(0.28)	(0.02)	(0.31)

Table 6: Payment Firm Returns and Central Bank Communication on CBDCs

This table shows the results from event study regressions. We rely on the BIS database from Auer, Cornelli, and Frost (2020) and define events as days on which there is communication on CBDCs from representatives of either the U.S. Federal Reserve, the ECB, or individual member countries of the Eurozone. The sample period is from January 2016 to June 2022. Event windows have a length of two days and include the trading day directly after an event day (as we do not know whether the communication happened before or after market closing). The dependent variable is the daily return of an index of payment firms. Payment firms are defined via the SIC code and the business description (see Section 2.1). *Positive Sentiment*, *Negative Sentiment*, and *Neutral Sentiment* are dummy variables. They respectively take a value of one if there is an event with a positive, negative, or neutral sentiment towards CBDCs on a given day and otherwise take a value of zero. *Market* is the daily market return (taken from Kenneth French's website). In Panel A columns (1) to (3), we only include one type of event dummy per regression at a time. In column (4), we include all three types of event dummies simultaneously. Column (5) only considers events associated with the Eurozone or individual member countries of the Eurozone. Column (6) only considers events associated with the U.S. In Panel B columns (1) and (2), we distinguish payment firms by 'Payee-Facing' firms (e.g., Fiserv, PayPal, Block/Square) and credit card 'Networks' (e.g., Visa, Mastercard). In column (3), we only consider communication in the form of speeches. Column (4) only considers communication from representatives that serve as President or Vice President (or an equivalent role) of their respective central banks. Column (5) only considers communication from representatives that do not serve as President or Vice President (or an equivalent role) of their respective central banks. The four rows at the bottom of each table indicate the number of events by event type in each regression specification. Robust *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Payment Firm Returns and Central Bank Communication on CBDCs

	(1) **Positive**	**(2)** **Negative**	**(3)** **Neutral**	**(4)** **All**	**(5)** **Euro Only**	**(6)** **U.S. Only**
Positive Sentiment	-0.0022**			-0.0022**	-0.0021**	-0.0034
	(-2.47)			(-2.44)	(-2.29)	(-1.19)
Negative Sentiment		0.0013		0.0012	0.0008	0.0026
		(1.48)		(1.34)	(0.86)	(1.47)
Neutral Sentiment			-0.0001	-0.0001	0.0001	-0.0015
			(-0.18)	(-0.14)	(0.16)	(-0.78)
Market	1.1847***	1.1853***	1.1851***	1.1849***	1.1851***	1.1847***
	(41.12)	(41.02)	(41.01)	(41.08)	(41.07)	(40.97)
Constant	0.0001	-0.0000	0.0000	0.0001	0.0001	0.0000
	(0.77)	(-0.00)	(0.15)	(0.66)	(0.58)	(0.22)
Observations	1,635	1,635	1,635	1,635	1,635	1,635
Adjusted R^2	0.7881	0.7873	0.7872	0.7879	0.7878	0.7874
# Positive Events	48	-	-	48	44	5
# Negative Events	-	13	-	13	9	4
# Neutral Events	-		52	52	46	7
# Total Events	48	13	52	113	99	16

Panel B: Robustness Tests – Payment Sector Subcategories, Type of Communication, and Seniority of the Central Bank Representative

	(1) Payee-Facing	(2) Networks	(3) Speeches Only	(4) Senior CB Representative	(5) Non-Senior CB Representative
Positive Sentiment	-0.0028**	-0.0019*	-0.0025**	-0.0032***	-0.0013
	(-2.45)	(-1.71)	(-2.47)	(-2.63)	(-1.10)
Negative Sentiment	0.0024**	0.0005	0.0008	0.0009	0.0014
	(2.10)	(0.48)	(0.69)	(0.41)	(1.39)
Neutral Sentiment	-0.0001	-0.0002	0.0007	0.0008	-0.0005
	(-0.07)	(-0.27)	(0.61)	(0.66)	(-0.51)
Market	1.2286***	1.1605***	1.1845***	1.1843***	1.1858***
	(42.13)	(34.11)	(41.00)	(41.00)	(40.99)
Constant	-0.0001	0.0003	0.0001	0.0001	0.0001
	(-0.24)	(1.13)	(0.35)	(0.41)	(0.34)
Observations	1,635	1,635	1,635	1,635	1,635
Adjusted R^2	0.7322	0.7012	0.7876	0.7878	0.7872

# Positive Events	48	48	44	36	12
# Negative Events	13	13	13	5	8
# Neutral Events	52	52	49	29	23
# Total Events	113	113	106	70	43

Table 7: Financial Firm Returns and Central Bank Communication on CBDCs

This table shows the results from event study regressions. We rely on the BIS database from Auer, Cornelli, and Frost (2020) and define events as days on which there is communication on CBDCs from representatives of either the U.S. Federal Reserve, the ECB, or individual member countries of the Eurozone. The sample period is from January 2016 to June 2022. Event windows have a length of two days and include the trading day directly after an event day (as we do not know whether the communication happened before or after market closing). The dependent variable is the daily return of the S&P 500 sector index Financials. *Positive Sentiment*, *Negative Sentiment*, and *Neutral Sentiment* are dummy variables. They respectively take a value of one if there is an event with a positive, negative, or neutral sentiment towards CBDCs on a given day and otherwise take a value of zero. *Market* is the daily market return (taken from Kenneth French's website). In Panel A columns (1) to (3), we only include one type of event dummy per regression at a time. In column (4), we include all three types of event dummies simultaneously. Column (5) only considers events associated with the Eurozone or individual member countries of the Eurozone. Column (6) only considers events associated with the U.S. The four rows at the bottom of each table indicate the number of events by event type in each regression specification. Robust *t*-statistics are reported in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Positive	**(2) Negative**	**(3) Neutral**	**(4) All**	**(5) Euro Only**	**(6) U.S. Only**
Positive Sentiment	-0.0003			-0.0003	-0.0006	0.0002
	(-0.37)			(-0.33)	(-0.66)	(0.04)
Negative Sentiment		0.0008		0.0008	-0.0003	0.0034
		(0.64)		(0.65)	(-0.26)	(1.36)
Neutral Sentiment			-0.0014*	-0.0014*	-0.0016*	-0.0015
			(-1.78)	(-1.78)	(-1.79)	(-0.99)
Market	1.0789***	1.0791***	1.0794***	1.0795***	1.0791***	1.0790***
	(39.97)	(39.97)	(40.01)	(40.00)	(39.95)	(39.96)
Constant	-0.0000	-0.0001	0.0000	0.0000	0.0001	-0.0001
	(-0.19)	(-0.35)	(0.13)	(0.15)	(0.28)	(-0.31)
Observations	1,635	1,635	1,635	1,635	1,635	1,635
Adjusted R^2	0.7274	0.7274	0.7279	0.7276	0.7276	0.7274
# Positive Events	48	-	-	48	44	5
# Negative Events	-	13	-	13	9	4
# Neutral Events	-		52	52	46	7
# Total Events	48	13	52	113	99	16

Appendix A: Payment Value Chain

Table A.1 below provides an overview of the parties involved in a retail payment process with credit or debit cards. Three key payment services are needed for a merchant to accept payment via credit or debit card:

- Acquirer/Processor: The acquirer/processor, A) provides a bank account where the payment is deposited, B) provides a POS-terminal (in-store) or a payment gateway (e-commerce) where cardholders swipe their cards or enter card details, C) processes the transaction to the card networks. Note that the acquirer can provide these services as a bundle; however, there are also many specialist companies that focus on part of the value chain.
- Network: The card networks (Visa, Mastercard, American Express, Discover) set the rules and standards and process the transaction from the acquirer to the card issuer, including authorization (for example, checking anti-money laundering and sanctions regulation), clearing and settlement (settlement between banks).
- Issuing bank: The issuing bank maintains the bank relationship with the cardholder and is involved in authorization (for example, checking for sufficient funds in the cardholders' bank account) and settlement (settlement within the bank, that is, deducting the amount from the cardholders' bank account).

Payment facilitators like PayPal, Stripe, and Square (now named Block) underwrite firms to accept (online) transactions. They essentially speed up the merchant onboarding process from weeks or days to just a few minutes. Formally, they sign up merchants as sub-merchants under their own merchant license, and therefore also bear the processing and fraud risk for their sub-merchants. Payment facilitators frequently offer additional services (such as PayPal's seller protection or Square/Block's card reader). Apple Pay and Google Pay have carved out part of the issuing banks' value chain. Interchange fees are heavily regulated across the world, while card scheme fees and acquirer markups are not.

Merchants bear credit and fraud risk of the cardholder if they decide to accept transactions without strong authentication (credit card number only, or credit card plus signature), while the issuing bank bears credit and fraud risk for payments with strong authentication (for example, where a PIN number is entered). The acquirer bears merchant credit risk and merchant fraud risk. If for example, the merchant sells a service (such as a flight) but does not provide the service, the cardholder can require a chargeback. Chargebacks are first borne by the merchant, however, if the merchant is not willing or not able to pay – which can be due to merchant credit risk or outright fraud on the merchant side – the acquirer must refund the cardholder.

Table A.1: Payment Value Chain

	Merchant (Payee)	Acquirer/Processor, Facilitator (Payee-facing)	Networks	Issuing Bank (Payer-facing)	Cardholder (Payer)
Key Function	· Sells goods and services	· POS-terminal (in-store) / payment gateway (e-commerce) · Acquirer processing[27] · Merchant bank account · Facilitator: underwrites firms to accept (online) payments	· Set rules and standards · Network processing[1]	· Issuer processing[1] · Cardholder bank account	· Buys goods and services
Credit and Fraud Risk	· Credit and fraud risk for transactions not verified via the issuing bank (e.g., card number only)	· Merchant credit risk[28]	· None	· Credit and fraud risk for transactions verified via the issuing bank (e.g., PIN, or 3D-secure)	· None (exception: gross negligence)
Fees	· Product price minus acquirer markup, scheme fees, and interchange fee	· Acquirer markup	· Scheme fees	· Interchange fee	· Product price
Fee Amount	· 50-350bps depending on payment method and location	Worldwide Ø: · *FIS:* 13bps · *Adyen:* 22bps · *PayPal:* 146bps[29] · *Square/Block:* 125bps	Worldwide Ø: · *Visa:* 19bps · *Mastercard:* 23bps · *American Express* and *Discover* not comparable[30]	U.S, and Europe Ø:[31] · U.S. Debit: 73bps · U.S. Credit: 174bps · Europe Debit: 20bps · Europe Credit: 30bps	· Not applicable
Examples	· *Walmart, Target, Wayfair, Etsy*	· POS-terminal: *Ingenico, Verifone* · Gateway and acquirer processing: *FIS, Chase Paymentech, Global Payments, Adyen* · Facilitator: *PayPal, Square/Block*	· *Visa, Mastercard*	· *Bank of America, Citigroup, Wells Fargo* · Other parts of the value chain: *Apple Pay, Google Pay*[32]	· Jane Doe, John Doe

[27] *Acquirer processing*: Merchant to Network and Network to Merchant. *Network processing*: authorization (e.g., AML and sanction laws), clearing, and settlement. *Issuing bank processing***:** authorization (e.g., availability of funds), settlement.

[28] Mainly chargeback-induced credit risk. Chargeback can occur for many reasons, a prominent one is consumer disputes. If a service was paid for but not received (e.g., because an airline goes bankrupt), then consumers can require a chargeback. If the merchant is unable to pay the chargeback, the acquirer needs to pay.

[29] Excluding pass-through (scheme fees, interchange fees). PayPal offers payment via a PayPal account that links email addresses to credit card and account numbers. Both PayPal and Square/Block provide further services to merchants (such as PayPal seller protection or Square reader).

[30] American Express and Discover act as acquirers, networks, and issuers. American Express, for example, earned USD 36.1 billion in revenue in 2020, equivalent to 361bps of their payment volume of 1.0 trillion.

[31] In the U.S., debit card interchange fees are limited by the Durbin Amendment, applicable to banks with over USD 10 billion in assets, to 21 cents plus 5bps of the transaction (plus 1bp for fraud-prevention measures). In Europe, consumer debit card fees are capped at 20bps, consumer credit card fees at 30bps.

[32] Services like Apple Pay and Google Pay sit between the issuing bank and the cardholder. These services promise to offer better customer satisfaction as well as lower fraud rates. The issuing bank typically passes part of the interchange fee to these service providers (initially 15bps in the U.S. for credit card transactions).