On the Rise of Payment Firms

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Abstract

Payment firms have experienced an exceptional growth over the past decade, with payment firms' market capitalization now exceeding the combined market capitalization of all banks in the U.S. We show that stock returns of payment firms are strongly correlated with stock returns of E-Commerce firms. Using three million observations at an online retailer, we provide micro-level evidence on the importance of payment firms for E-commerce purchases. When a customer's preferred payment type is not seamlessly available, approximately a quarter of customers abandon the purchase instead of switching to a different payment type. We document this strong clientele effect both for credit cards, PayPal, as well as Buy-Now-Pay-Later (BNPL) products. Our results suggest that – although E-Commerce firms have access to many payment types – each payment firm has a significant bargaining power vis-à-vis E-Commerce firms.

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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. As of 2020, the combined market capitalization of all payment firms exceeds the combined market capitalization of all banks in the U.S.[1] This is in stark contrast to just ten years ago, when payment firms accounted for only one fifth of the combined market capitalization of banks. The combined market capitalization of payment firms also exceeds the combined market capitalization of all insurance companies, and it exceeds the combined market capitalization of all other financial firms (such as brokers, dealers, and non-depository institutions). In this paper, we (i) document the rise of payment firms over the past decade, (ii) associate the rise of payment firms with the rise in E-commerce, (iii) provide micro-evidence on the importance of payment firms for E-commerce sales.

To document the rise of payment firms, we start by providing a method to identify and classify payment firms. Using standard industry codes such as SIC or NAICS, payment firms are spread across various industries, ranging from financial services, to information technology, E-commerce, and even manufacturing subsectors ("calculating and accounting machines").[2] We develop a method to classify firms as payment firms based on a combination of a firms' 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 the payment sector.

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[1] We define banks as those firms whose SIC code starts with 60 (depository institutions) and which are not payment firms. The market value of non-depository institutions (SIC code starting with 61) makes up less than 10% of the market value of banks and we classify them as "other".

[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 among software and services related to processing payments, is classified under the SIC code 3578 ("Computer and Office Equipment / Calculating and Accounting Machines").

Following this classification, we document three key descriptive facts: first, the payment industry now accounts for 28.5% of the finance sector market capitalization, exceeding the share of banks (27.7%), insurance companies (22.2%) and other financial firms such as brokers, dealers, and non-depository institutions (21.6%). The share of the payment industry has steadily increased from 5.9% (1990), 5.0% (2000), 8.8% (2010) to 28.5% (2020). Three of the most valuable financial firms in the U.S. are now payment firms (Visa, Mastercard, PayPal), with only one bank (J.P. Morgan) and one insurance company (United Health) left in the top 5. Second, the profitability of payment firms has increased threefold over the 1990-2020 period (RoA of 1.4% in the 1990s to 4.5% in the 2010s, RoE provides a similar picture) and now stands at four times the profitability in the rest of the financial sector.

In the next step, we associate the rise of payment firms with the growth of E-Commerce. We document a strong co-movement of payment firms' stock returns with stock returns of E-Commerce firms. We augment a five-factor Fama-French model with a factor that is long E-Commerce firms and short Brick-and-Mortar stores. Payment firms' stock returns significantly load on the E-Commerce-minus-Brick-and-Mortar factor. This analysis provide suggestive evidence for the importance of the rise of E-Commerce for the rise of payment firms.

In the third step, we provide micro-level evidence on the importance of payment firms for E-Commerce transactions. How dependent are E-commerce sales on the availability of a particular payment type? What happens if an E-commerce firm does not offer a customers' favorite payment type? Do customers seamlessly switch to a different payment type when this is available at no extra (monetary) costs? Or do E-commerce firms suffer a loss in revenue if they do not offer a customers' favorite payment type? These questions are important to understand the value that payment firms add for E-commerce firms; they are important to understand the bargaining power of payment firms; and they can inform us about the reasons for the rise of payment firms.

We access 3 million observations from a German E-Commerce firm that sells furniture online. Our data contains payment options offered by the E-Commerce firm as well as payment choices made by customers. Customers are typically offered a menu of payment types, with the most frequently payment types used being Buy-Now-Pay-Later (BNPL) (51%), PayPal (29%), and credit cards (10%), followed by prepayment (9%) and installment credit (1%).

Availability of PayPal, credit cards, as well as BNPL payment is subject to exogenous shocks: PayPal cannot be used during technical outages (which are rare but do exist). Credit card payments typically work by simply entering the credit card number. However, customers that exceed a threshold in an internal transaction risk score must enter a PIN number which significantly restricts the use of credit cards. Buy-Now-Pay-Later is only offered to customers that score above a predefined creditworthiness cut-off.

Using these shocks to the availability of payment types, we document a strong clientele effect: A quarter of customers that wanted to use a credit card abandon the purchase after being asked for a PIN, even though all other payment types are available to them at no extra (monetary) cost. Approximately a quarter of those customers that typically use PayPal abandon the purchase when PayPal is not available during a technical outage. Exploiting the discontinuity that governs availability of Buy-Now-Pay-Later (BNPL), we document that one third of customers that would have otherwise used BNPL abandon the purchase when BNPL is not offered. Overall, approximately three quarters of customers substitute to other payment types when their favorite payment type is not available, while roughly one quarter simply abandons the purchase. Taken together, these results suggest that the availability of a customers' favorite payment type is of crucial importance in E-commerce, with sales suffering significantly when E-commerce firms reduce the menu of payment options available to customers.

These results imply that payment firms have a significant bargaining power vis-à-vis E-commerce firms. While most E-commerce firms offer a menu of around 5 or more different payment options, each payment provider wields a significant market power vis-à-vis E-commerce firms. The clientele mechanism helps to explain the concurrent rise of several payment firms, and the large market capitalization of each of these payment firms.

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[3], the adoption and use of cash vis-à-vis other payment types[4], the regulation of fees that banks earn from payment transactions[5], or on household finance related topics on the use of credit cards.[6] In contrast, our paper sketches the rise of payment firms over the past decade, links the rise in payment firms to the rise of E-Commerce, and provides micro-level evidence on the bargaining power of payment firms in the E-Commerce sphere.

A recent strand of the literature has analyzed the competition of FinTech payment firms with traditional banks. Parlour, Rajan, and Zhu (2021) develop a model where FinTech payment providers disrupt informational flows to traditional banks and thus affect traditional banks' lending business. Ghosh, Vallee, and Zeng (2021) empirically document the informational synergies between cashless payments and lending. The evidence in these papers is consistent with our evidence on the negative correlation of payment firms' with banks' excess stock return. While these papers analyze the interplay of payment firms with banks, we analyze the interplay between payment firms and E-Commerce. In particular, we document that the rise of payment firms over

[3] See for example Baxter (1983), Katz (2001), Rochet and Tirole (2002), Rochet and Tirole (2003). Shy and Wang (2011).

[4] 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), and Brown, Hentschel, Mettler, and Stix (2021).

[5] See, for example, Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), Jambulapati and Stavins (2014), or Kay, Manuszak, and Vojtech (2018).

[6] See, for example, 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).

the past decade is closely associated with the rise in E-Commerce, and provide micro-level evidence on the bargaining power of payment firms vis-à-vis E-Commerce firms.

2. The Rise of Payment Firms: Descriptive Evidence

2.1 Definition of Payment Firms and Creation of Data Set

Our data covers the 1990-2020 period. It is based on listed firms located in the U.S. with a SIC-code starting with 60 (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:

i. the Compustat business description contains at least one of the words "payment" or "merchant solution".

AND

ii. the firm has a SIC-code of 6099 (*Functions related to Depository Banking*; examples: Visa, Mastercard), 6141 (*Personal Credit Institutions*; examples: American Express, Discover), or a SIC code that does not start with 6.

The latter condition ensures we are not picking up financial firms where payment might be only one of many business lines. We cross-check our definition with industry reports from Nilson – the key provider of statistics on the payment industry – and find that our definition has a 95% overlap with the subjective common-sense definition used in these industry reports.[9] Our definition yields 116 payment firms. Out of these 116 payment firms, 71 firms have a SIC code

[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 is less than 3% of the finance sector market capitalization, and we therefore decided to subsume non-depository institutions under one category together with brokers and dealers.

[8] Note that Compustat does not classify single firms as bank holding companies (SIC codes 6712). Firms that are classified in CRSP as bank holding company (SIC code 6712) are typically classified as depository institutions in Compustat (SIC code starting with 60).

[9] 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 1.640trn, while the definition from Nilson results in a payment sector market capitalization of USD 1.690trn, of which USD 1.621trn are overlapping with our definition.

starting with 73 (*Business Services*; examples: PayPal, Square), 15 firms have a SIC code 6099 (*Functions related to Depository Banking*, examples: Visa, Mastercard), 3 firms have a SIC code 6141 (*Personal Credit Institutions*; examples: American Express, Discover), and 27 firms have other SIC codes. Appendix A provides a detailed overview about the companies involved in (retail) payments as well as their respective roles. We compute the market capitalization from Compustat using end-of-calendar-year values for the share price (*prcc_c*) multiplied by shares outstanding (*csho*). As of 2020, the market capitalization of payment firms is concentrated in SIC code 6099 (51%), SIC codes starting with 73 (41%), and SIC code 6141 (8%), with the remaining SIC codes accounting for less than 1% of the aggregate market capitalization of all payment firms.

2.2 Payment Firms' Share of the Finance Sector Market Capitalization

Figure 1 provides the share of the finance sector market capitalization by subsector from 1990-2020. In 1990, banks (35%) and insurance companies (47%) 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, the market capitalization of payment firms exceeds the market capitalization of banks, with payment firms accounting for 28.5% of finance sector market capitalization, followed by banks (27.7%), insurance companies (22.2%), and brokers, dealers, and non-depository institutions (21.6%). The rise of payment firms is mostly driven by the 2005-2020 period, where payment firms' market capitalization increased from USD 140bn to USD 1,640 bn and their share of the financial sector market capitalization increased more than sixfold from 4.4% (2005) to 28.5% (2020).

Table 1 depicts the largest firms for each of the four finance subsectors. The largest payment firms by market capitalization in 2020 are Visa (USD 465bn), Mastercard (USD 355bn), and PayPal (USD 275bn). Three of the most valuable financial firms in the U.S. are now payment firms (Visa, Mastercard, PayPal), with only one bank (J.P. Morgan, USD 387bn) and one insurance company (United Health, USD 332bn) left in the top 5.

The rise of payment firms is, however, not limited to Visa, Mastercard, and PayPal. The 8th largest payment firm (Global Payment, USD 64bn) is more valuable than the 8th largest bank (BNYM, USD 38bn), the 8th largest insurance company (Travelers, USD 35bn), as well as the 8th largest broker, dealer, and non-depository institution (Blackstone, USD 44bn). To be clear, market capitalization can and should not be equated with importance for the financial system, nor with importance for the economy. However, the growth in the market capitalization of payment firms over the past 15 years has been remarkable, and there is little research on the drivers and consequences of this rise of payment firms.

2.3 Profitability of Payment Firms

Panel A of Figure 2 shows that the rise in payment firm market capitalization is associated with a rise in profitability of payment firms. The average Return on Assets (RoA) of payment firms over the 2010s was 4.5%, more than twice the profitability over prior decades (1990s: 1.4%, 2000s: 2.4%), and more than four times the average profitability in other financial sectors in the 2010s (banks: 0.9%, brokers, dealers, and non-depository institutions: 0.7%, insurance companies: 1.2%). This rise in profitability vis-à-vis other financial sectors is robust to a) looking at other proxies for profitability (Return on Equity, or profit margin), b) excluding the financial crisis years, as well as removing the Corona episode, and c) winsorizing Return-on-Assets to remove the influence of outliers (results are available upon request).

Panel B of Figure 2 depicts the development of market-to-book ratios across financial sectors. Payment firms have witnessed a rise in their market-to-book ratios over the last decade: Payment firms had an average market-to-book ratio of 7.47 in 2020, more than five times the market-to-book ratio of banks (1.15), and significantly higher than the market-to-book ratio of insurance companies (1.52) and of brokers, dealers, and non-depository institutions (2.23). A rise in market-to-book ratios is a direct consequence of the expansion of profit margins in standard valuation models. Overall, this evidence suggests that payment firms' rise in market capitalization has been associated with a rise in profitability. At the end of our sample period, both profitability and market-to-book ratios of U.S. payment firms have reached levels unprecedented in the past decades, and unprecedented in other financial sectors.

2.4 Payment Firms and the Rise of E-Commerce

Casual observations suggests that payment firms benefit from the rise in E-Commerce and the associated shift towards digital payments: First, various industry reports highlight the importance of E-Commerce growth for the rise in payment firms.[10] Second, the most recent annual reports of the ten largest payment firms include the word "E-Commerce" 63 times – compared to 5 times for the largest ten banks – and payment firms typically mention the future development of E-Commerce as a key business risk.[11]

To analyze the relationship between E-Commerce and payment firms more thoroughly, we investigate the co-movement of payment firms' stock returns with the stock returns of various economic sectors. In particular, we regress the long-short return of an index of payment firms on (i) the long-short return of an E-Commerce index as well as (ii) the long-short returns for each of the S&P 500 industry sectors. The long-short return is defined as the total stock return (including dividends) of the respective index minus the total return on the S&P 500 index. The use of long-short returns ensures that we pick up co-movement beyond a pure co-movement with the overall

[10] BCG (2021) lists E-Commerce adoption as one of the two key drivers of revenue growth in the payment industry. See McKinsey (2020) for a similar analysis.
[11] For example, PayPal states in its most recent annual report "While our business has benefited from the shift […] towards e-commerce and digital payments, to the extent that customer preferences revert to pre-COVID-19 behaviors […] we would be adversely impacted."

market. We construct an index of payment firms using our definition of payment firms (see Section 2.1) and determining monthly value-weighted return of all payment firms. As E-Commerce index, we choose the Dow Jones Internet Commerce Index which is available since 2004.[12] Our sample period ranges from 2004-2021.

Panel A of Figure 3 provides the results. A 1% increase in E-Commerce long-short returns is associated with a 0.30% increase in payment firms' long-short returns. Furthermore, payment firms' stock returns are more sensitive to E-Commerce stock returns than to any other economic sector. In contrast, long-short returns of the finance sector (excluding payment firms) have the largest co-movement with industrial and the real estate sector (see Panel B of Figure 3).

Table 3 provides a more formal analysis of this relationship. We estimate a time series regression of the excess return of payments firms on the Fama-French five factors (Fama and French, 2015) to obtain the respective factor risk exposures (betas):

$$R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \qquad (1)$$

where *Rit* are monthly returns of an index of payment firms, *RFt* are 1-month T-Bill returns, and (*RMt-RFt*), SMB, HML, RMW, and CMA are the factors from the five-factor Fama-French model. Column (1) of Panel A in Table 2 shows that payment firms have a market-beta of approximately one (1.136), they have a negative loading on the CMA-factor (consistent with payment firms being high investment firms) and insignificant loadings on the other factors.

We augment the five-factor model using an "E-Commerce minus Brick-and-Mortar" (*EMB*) factor that captures the returns of E-Commerce firms minus the returns of Brick-and-

[12] This index includes, for example, Amazon, Alphabet, Facebook, AirBnB, Expedia, Wayfair, and Etsy. There is no E-Commerce subindex of the S&P 500 index, instead, these firms are either part of the S&P sector Consumer Discretionary or Communication Services.

Mortar stores. For E-Commerce firms, we rely on the Dow Jones Internet Commerce Index; we proxy the return on Brick-and-Mortar stores using the average returns of the two S&P 500 consumer subsectors (Consumer Discretionary and Consumer Staples).[13]

Column (2) of Panel A in Table 2 provides the results. Payment firms have a significantly positive loading on the EMB factor: when E-Commerce firms outperform Brick-and-Mortar stores by 1%, payment firms outperform by 0.244% (significant at the 1 percent level). Column (3)-(4) document that the results are robust to excluding the financial crisis (2008/2009) or excluding the Corona episode (2020/2021). In column (5), we refine the definition of Brick-and-Mortar stores. The S&P 500 consumer subsectors include both producers of consumer products (for example, Coca Cola) as well as consumer-facing businesses that directly sell to consumers (such as Walmart, Target, and Starbucks). In column (5), we refine Brick-and-Mortar returns using only the GICS Industries *Food & Staples Retailing*, *Multiline Retail*, *Specialty Retail*, and *Hotel, Restaurants & Leisure*. Again, results are robust. Results are also robust to using the CAPM, the Fama-French three-factor model (Fama and French, 1992) or the Carhart-4-Factor model instead of the Fama-French five-factor model (results are available on request).

Panel B repeats the analysis using stock returns of Financials (excluding payment firms) instead of payment firms as the dependent variable. In contrast to payment firms, financials have a (weak) negative loading on the EMB factor.

Taken together, the stock return analysis supports the idea that payment firms' stock returns are closely associated with the stock returns of E-Commerce firms. In the following section, we provide micro evidence on the importance of payment firms for E-Commerce transactions.

[13] Note that the S&P 500 consumer subsector also include some E-Commerce firms. A portfolio that is long E-Commerce and short the S&P 500 consumer subsector will, however, be positively correlated with E-Commerce returns and negatively correlated with Brick-and-Mortar returns, which is our key goal.

3. The Importance of payment firms for E-Commerce: Micro-evidence

3.1. Data and institutional setting

To understand how important individual payment options are on the micro level, we analyze data from a German online retail company. This retailer sells furniture through its own website. We have access to 3 million observations of between January 2016 and June 2021.

Customers browse the website, place one or more items into their shopping cart, and proceed to a check-out site where they view all available payment options. Prices do not depend on the payment option chosen. Not all payment options are available to all customers (details will be discussed below). We observe information about the available payment options, customer characteristics, the shopping items, and whether their website visit is successfully converted into a purchase order ("conversion" in the following) or not. In Figure 4 we plot the monthly fraction of all payment methods used by customers over time. The most important payment type with about 51% is Buy-Now-Pay-Later (BNPL), followed by PayPal (29%), credit card (10%), prepayment (9%), and installment (1%). Tables A.2 and A.3-A.5 in the appendix contain a list with a detailed description of all variables used and their summary statistics for the estimation samples in this study.

In the microeconomic analysis we follow different approaches for each of the payment options we analyze, corresponding to different sources of exogenous variation. In the following three subsections we describe these settings, the corresponding identification strategies, and the empirical results. The explanatory variable of interest in all analyses using micro data from the online retailer is the conversion likelihood, coded as a dummy that is equal to one if there is a successfully completed purchase and zero otherwise.

We hypothesize that there should be a significant number of customers that have their preferred payment methods and tend to stick to these due to convenience and familiarity. A decrease in the availability or in the ease-of-use for the preferred payment method should then have a considerable adverse impact on the number of customers finalizing a purchase. Alternatively, one might believe that the availability of other payment options on the retailer's website, such as PayPal or BNPL, should be sufficiently convenient and easily accessible substitutes for a payment option like credit card, preventing any significant negative effect on conversion likelihoods when using a credit card becomes less convenient.

3.2. Credit Card Payment

Setting

We focus on the period between February 2018 and January 2021. During that time, a customer would first visit the check-out website, then select a payment method of choice. Those selecting credit card are required to enter payment details. After this, the retailer computes an internal transaction risk score and uses it to decide whether to request an additional identity verification. If this is not requested, the customer confirms the purchase in a final step by clicking on a confirmation button.

If additional identity verification is requested, the customer is redirected to the bank's website providing the credit card. He or she is then required to verify the identity by entering a personal password associated with their personal banking account to which the credit card is linked.[14] The additional verification requirement is interesting in this analysis, because it reduces the ease and convenience of a credit card transaction. Customers might have to look up information they wrote down elsewhere or even fail to remember and look it up all together.

[14] This usually involves logging in at the bank's website and confirming the purchase at the bank, entering some piece of information known by the customer and previously saved by the card providing bank, or entering a temporary non-reusable PIN code sent to a personal device owned by the customer. This process is known as "3-D Secure" or "Verify by Visa". Once this process is successfully completed, the customer will have to finally confirm the purchase by clicking on the confirmation button.

The decision to request an identity verification during this period is made by the retailer and is primarily a function of the internal transaction risk score. This score is designed to detect the likelihood of fraud in credit card payments, such as the use of stolen credit card information. The score is computed in real time from information obtained by the digital footprint a customer leaves behind, such as the device or the email address used. It is computed for all customers reaching the final check out page and choosing to pay by credit card. Accordingly, the sample in the analysis in this subsection covers only the pool of customers selecting credit card as a payment option.[15] We exclude returning customers, for which the score is not used. The score ranges from 0 to 1, with a higher score indicating a higher likelihood of fraud. *All* those customers above a value of 0.7 are required to verify their identity. *Almost all* (~97%) customers below the threshold value are not required to do so. Figure 5 illustrates this.

Identification

We exploit the discontinuity in the likelihood that the retailer requests identity verification at 0.7 for a fuzzy RDD. It estimates a local average treatment effect (LATE) of requesting an identity verification for customers intending to pay by credit card with an internal transaction risk score close to the threshold. In Panel A, Figure 6 we model the likelihood of a verification request as a function of the distance between the score and the threshold value, showing an almost sharp RDD, where the likelihood of a verification request jumps from less than 5% to 100% when crossing the threshold value of 0.7. In Panel B we show that the conversion likelihood of a shopping visit into an actual purchase drops from about 76% to around 54% at the discontinuity. For our regression analysis, we first estimate equation

[15]In the two following subsections we do not analyze only those customers indicating to select a specific payment method.

$$T_{i,t} = \alpha_1 \underline{S}_{i,t} + \alpha_2 S_{i,t} + \alpha_3 \underline{S}_{i,t} \times S_{i,t} + \alpha 4 X_{i,t} + \eta_w + \sigma_c + \varepsilon_{i,t} \quad (1)$$

where $T_{i,t}$ is the treatment dummy (equal to one if addition verification is required and zero otherwise); $\underline{S}_{i,t}$ is an indicator variable for whether the internal transaction risk score is above the score threshold; $S_{i,t}$ is the score-point distance between the threshold and the customer's score, $X_{i,t}$ are customer and website visit controls; η_w and σ_c are week and county fixed effects; standard errors $\varepsilon_{i,t}$ are clustered by score bins (separated by 100 percentiles).

In the second step we explain the likelihood that a customer intending to pay by credit card completes a visit with a purchase (dummy variable $Y_{i,t}$) from the predicted treatment dummy variable $T^{i,t}$ via equation

$$Y_{i,t} = \beta T^{i,t} + \delta_1 S_{i,t} + \delta_2 \underline{S}_{i,t} \times S_{i,t} + \delta_3 X_{i,t} + \eta_w + \sigma_c + \mu_{i,t} \quad (2)$$

The system of the two equations is estimated via 2SLS, akin to a setting where the treatment is instrumented with the threshold (Hahn, Todd & Van der Klaauw, 2001). We apply an optimal bandwidth selector with a triangular kernel function, restricting the estimation sample to the narrow bandwidth around the threshold.[16] The coefficient of interest is β from equation 2, which we interpret as the LATE.

The no-manipulation assumption of the forcing variable is required to hold for identification. In Panel C in Figure 6 we show that there is no spike in the distribution of observations just below the threshold. This reassures our expectation that the score values do not suffer from manipulation: customers are unlikely to be aware of the existence of this internal transaction risk score, or of details on how this score is computed.

[16]The optimal bandwidth is +/- 0.227 score points.

Results

Results are in Table 3. Kleibergen-Paap Robust F-Stats are extremely high, reflecting the almost sharp discontinuity at the threshold. Coefficients of the predicted identity verification request variable imply that 25% of customers that intend to pay via credit card abort the process and do not purchase anything rather than switching to a different payment method when the retailer requires an identity verification (coefficients are robust against alterations in the regression specification and significant at 1%).[17]

For further interpreting the coefficients, it is important to keep in mind that around 10 out of 100 customers usually use a credit card to pay for a purchase at the retailer. The discussed regression coefficient then implies that around 2-3 out of these 10 customers abort their purchase process if all customers intending to pay by credit card were to be asked for an additional verification check. This inconvenience using credit card is thus a sizable effect on sales at E-commerce companies. In the appendix we show that our results are similar when we widen or narrow the bandwidth around the threshold by 10%.

3.3. PayPal

Setting

The E-commerce company offers PayPal as a payment option for all customers. As a source of exogenous variation in the availability of PayPal, we make use of technical outages. These are rare but do happen. We do not directly have an indicator of PayPal outages in our data set. Instead, we build a proxy for PayPal outages from Google search requests. In particular, we

[17]For simplicity, we assume that our LATE is in fact an ATE. We also ignore that around 4% of customers in the control group are "treated".

scrape all hourly Google search requests for problems at PayPal ("PayPal Störung") in Germany for the period of the analysis.[18] In Figure 7 we plot the resulting hourly Google search index over time. It is striking that relatively few hours stick out significantly.

Identification

Since we are interested in significant outages at PayPal, we focus on the extreme upper tail of the distribution of the search index, defining all hours above the 99.5th percentile as a "PayPal Outage" with a dummy variable (variable Z_h in Equation 3) that is equal to one in such cases. We assume that there are no technical problems during all other hours (Z_h taking a value of zero) but exclude those between the 99.5th and the 95th percentiles.[19] Our proxy is only a fuzzy proxy for the availability of PayPal. Indeed, we observe that payment via PayPal decreases by approximately 10% during PayPal outages, but many customers are still able to use PayPal when our fuzzy proxy of PayPal outages is equal to one.

We assume it is unlikely that technical problems at the dramatically larger company PayPal are caused by any type of activity at our online retailer (reverse causality), or that both are determined by a third factor. While heavy internet traffic may be associated with such problems, we do include week fixed effects. Results are also robust to using date and hour-of-day fixed effects. If these assumptions are true, then using a proxy for these problems to explain conversions at the retailer in a regression analysis should allow us to recover a causal effect on conversion likelihoods at the retailer. However, a mayor caveat is that we do not know how many customers are actually "treated" – neither during hours we define as PayPal outages, neither during those we assume to be periods without any technical problems at PayPal. If any common

[18] The raw index is scaled to 100 as the highest value in the period downloaded – which is a maximum of 6 months for hourly data at Google Trends. To construct an index with consistent scaling throughout the entire period, we downloaded overlapping periods, started from the first 6 months, then added periods consecutively, calculated the ratio of indexes for the same non-zero hours in the overlapping period, and used this ratio to scale the added index. We repeat this procedure until the entire period is constructed.

[19] These definitions do not drive our results. Similar results without excluding a bandwidth are available upon request.

time pattern should drive our results, they should not be robust against date and hour-of-day fixed effects that yield similar results in auxiliary regressions in the online appendix.

In the regression analysis we use this Google search based PayPal outage variable to explain the likelihood that a customer's visit of the retailer's check-out website is converted into a purchase (dummy variable $Y_{i,t}$) via equation

$$Y_{i,t} = \beta Z_h + \delta X_{i,t} + \eta_w + \sigma_c + \varepsilon_{i,t} \tag{3}$$

where all variables are defined as in Equations 1 and 2 above. In this equation here, standard errors $\varepsilon_{i,t}$ are clustered by hour (the level on which our treatment occurs).

Results

Results are in Table 4. Depending on the specification, coefficients suggest that at least 3 out of 100 customers abort their purchase at the retailer when at least some customers interested in using PayPal are more likely to experience technical problems using this payment method (all estimates are highly significant). Thus, sales of the E-commerce company are considerably impacted by the availability of PayPal as a payment option.

Since only around 30 out of 100 customers use PayPal in our sample, this suggests a relatively large economic magnitude. Three out of 30 customers (i.e., 10%) that usually pay using PayPal abort without a purchase. We do not have any information about the exact number of customers that actually do experience problems. If we assume that half of all customers have problems using PayPal, then at least 20% of customers that usually would have paid with PayPal abort the purchase when they cannot use PayPal due to an outage.

In the appendix we present similar results where we change the extreme value definition in Google searches to the 99.9th or 99.0th percentile of the distribution. We also show that our results hold when we use extremely low values (1.5st percentile) in the distribution of average hourly PayPal shares in total conversions at the online retailer to define a PayPal outage. Available upon request are equivalent results where we include higher fixed effects dimensionality with zip code, date, and hour-of day fixed effects.

3.4. Buy-Now-Pay-Later (BNPL)

Setting

The most important payment options for customers of this retailer is Buy-Now-Pay-Later (BNPL).[20] When customers select this payment option they receive an invoice together with the purchased items once they are sent to the customer. Terms require customers to pay the bill 14 days upon delivery. The setting differs from the analysis of credit card verification in that the retailer requests an external credit score together with a digital footprint to decide whether to offer BNPL as a payment option *before* these payment options are presented to the customer.[21] The "treatment" in this subsection is thus the online retailer's decision to offer BNPL as a payment option. We analyze the pool of all customers, not just those that are interested in this particular payment option.

In the period of analysis between January 2016 and April 2018, the retailer developed and tested the decision function and altered cut-off thresholds, resulting in 4 different thresholds for the score, used at different points of time for all customers. Figure 8 illustrates this. It displays the external credit scores of all those customers receiving a BNPL payment offer in the score range of interest. Since there was no binding external score threshold between July 18th and August 1st,

[20] Buy-Now-Pay-Later refers to invoice payments in our setting. Some also subsume installment payments as BNPL. However, installment payments play a less important role at the E-commerce company we analyze.
[21] See Berg, Burg, Gombović, and Puri (2020) for details on credit scoring using digital footprints.

2016, we exclude this latter period and also all customers that previously made a purchase from the analysis since they are handled differently.

Identification

We exploit the discontinuities in the company's decision-making function for a fuzzy RDD that calculates the LATE of receiving a BNPL offer for a customer with a credit score equal to the threshold.

As in the analysis of credit card verifications, we model the likelihood that the retailer offers BNPL to a customer in shopping session i at time t via treatment Equation 1, with the exceptions that the treatment dummy $T_{i,t}$ now represents a BNPL offer; $\underline{S}_{i,t}$ becomes an indicator for whether the credit score is above the respective credit score threshold (1) or not (0); $S_{i,t}$ is now a credit score-point distance; standard errors are clustered by credit score bins (separated by 100 percentiles).[22] Using Equation 2 we then explain the likelihood that a potential customer completes a purchase during the website visit in which he or she checked out and viewed the payment options.

It is noteworthy that there are no-shows (Bloom, 1984), that is, eligible customers above the threshold not receiving BNPL offers. This is illustrated by Panel A, Figure 9. The probability of receiving a short-term loan offer jumps from 0% just below the thresholds to approximately 40% for the external score just above the threshold. Panel B shows that the likelihood of using BNPL jumps from 0% to 25% and Panel C that the likelihood of a conversion increases by around 6 percentage points at the threshold (from around 67% to 73%). In Panel D we see from the distribution of credit scores around the threshold that there is no evidence for manipulation.

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[22]The optimal bandwidth is +/- 122 score points.

Results

Results are in Table 5. Kleibergen-Paap F-statistics or 38-60 suggest a valid first stage. Coefficients imply that at least 15 out of 100 average customers abort their purchase when the online retailer chooses not to offer BNPL (all coefficients are significant at the 5% level).

Throughout our sample period, only 50 out of 100 customers use BNPL on average. This implies that 15 out of 50 customers that typically use BNPL (or 30%) do not purchase an item when this payment option is not available.

In the appendix we show that our results are equivalent when we widen or narrow the bandwidth around the threshold by 10%. Available upon request are equivalent results where we include higher fixed effects dimensionality with zip code, date, and hour-of day fixed effects.

4. Conclusion

In this paper, we have documented the rise of payment firms over the past decade. We show that the rise of payment firms is closely related to the rise in E-Commerce. While excess stock returns of payment firms are positively correlated with excess stock returns for E-Commerce firms, they are negatively correlated to excess stock returns of financial firms.

Using micro-level data from a German E-Commerce firm, we document the importance of payment firms for E-Commerce sales. Even though the E-Commerce firms offers a menu of 5-10 payment types, customers have their preferred payment type and are reluctant to switch to different payment types. When a customers' favorite payment types is not available, between a quarter and half of customers abandon the purchase instead of switching to a different payment type. Overall, our results point to a significant bargaining power of payment firms in the E-Commerce sphere. The concurrent bargaining power of several payment firms in the E-Commerce sphere contributes to the rise of payment firms over the past decade.

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Figure 1: Share of Finance market capitalization by subsector

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 1 for each year.) The data is based on U.S. listed firms with a SIC-code of 60 (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 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 1990-2020. Market capitalization is taken from Compustat using end-of-calendar-year values for the share price (prcc_c) multiplied by shares outstanding (csho). Source: Compustat.

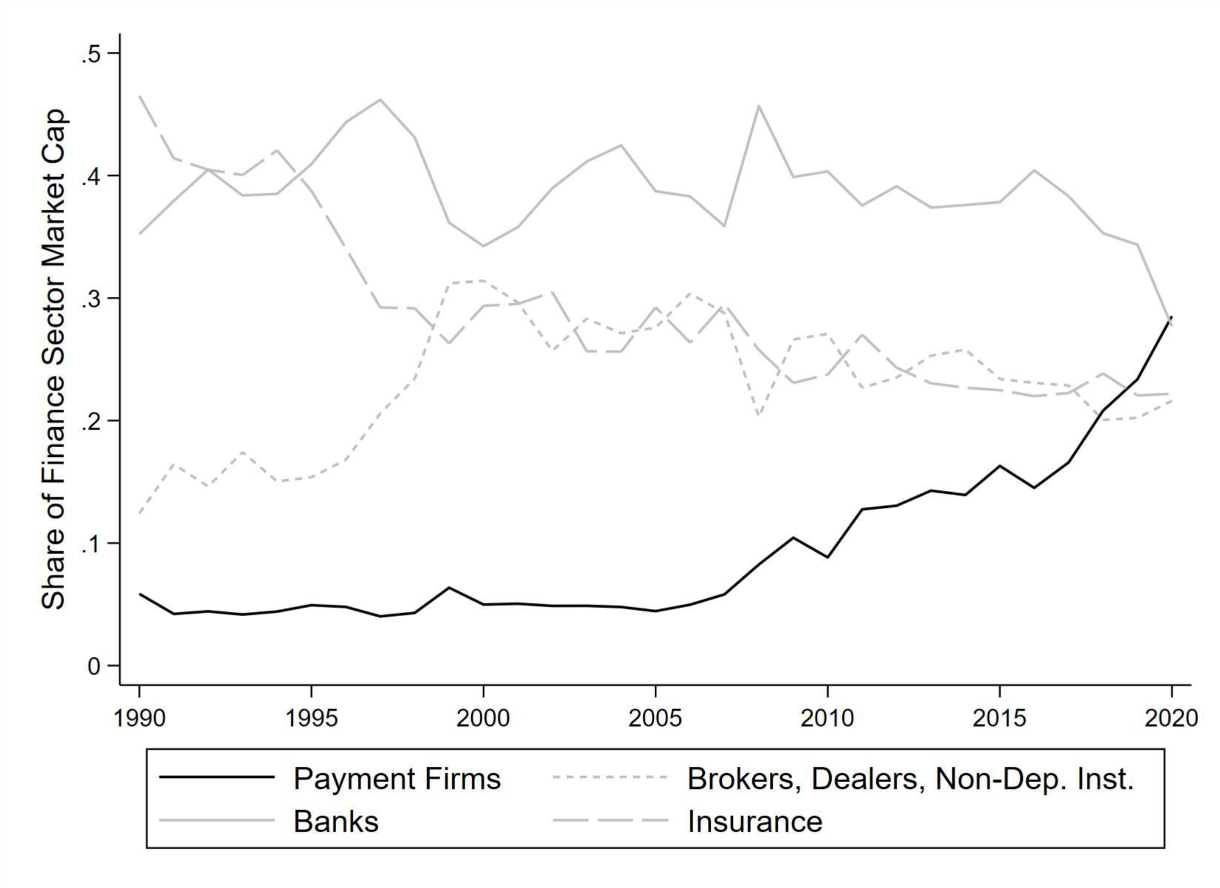
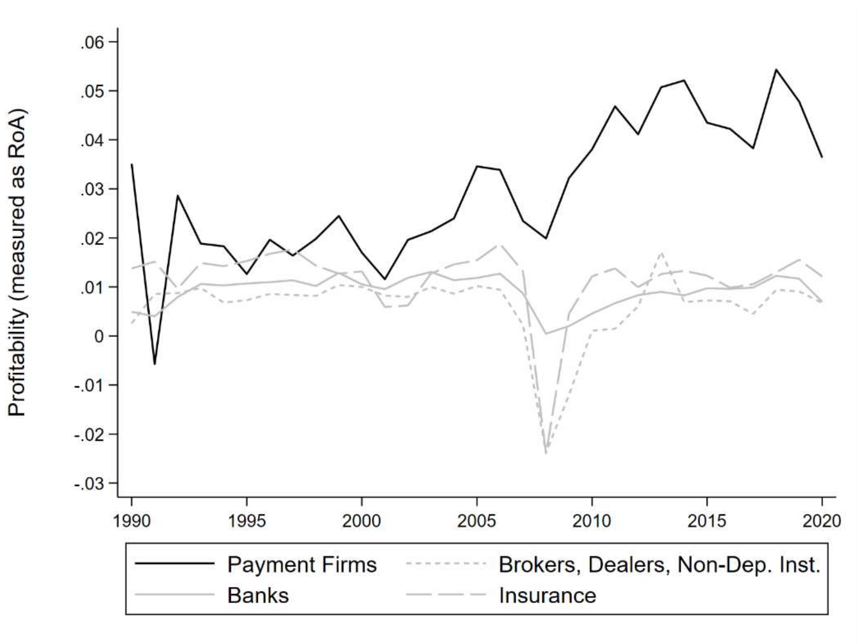


Figure 2: Profitability and Market-to-Book

This figure shows the profitability and market-to-book ratio for subsectors of finance in the U.S. See Figure 1 for a definition of Finance subsectors. Profitability is measured as the return on assets (RoA), that is, the sum of net income divided by the sum of total assets in a subsector. The market-to-book ratio is measured as the sum of the market capitalization (prcc_c · csho) divided by the sum of book value of equity (ceq) in a subsector. The sample period is from 1990-2020. Source: Compustat.

Panel A: Profitability by Finance subsector



Panel B: Market-to-Book ratios by Finance subsector

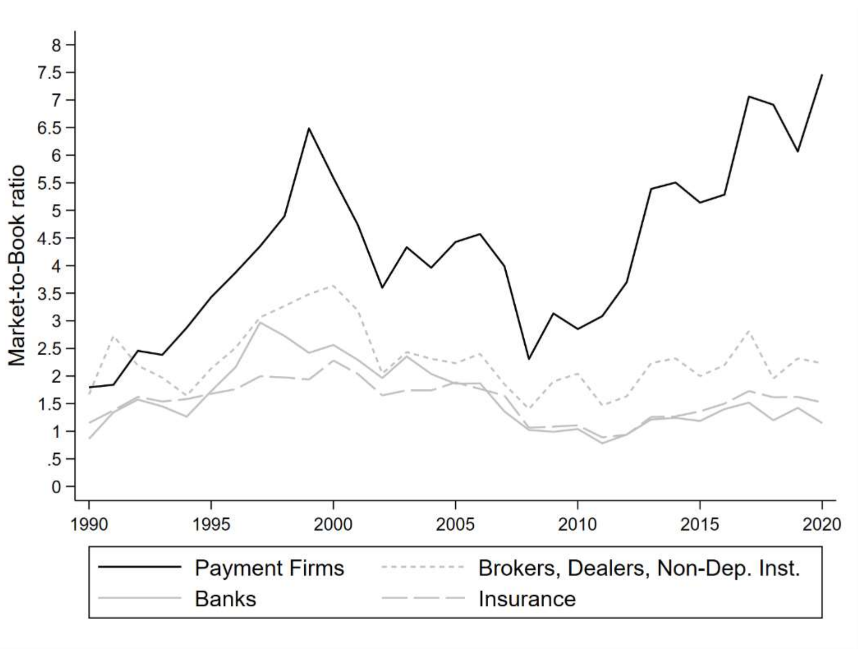
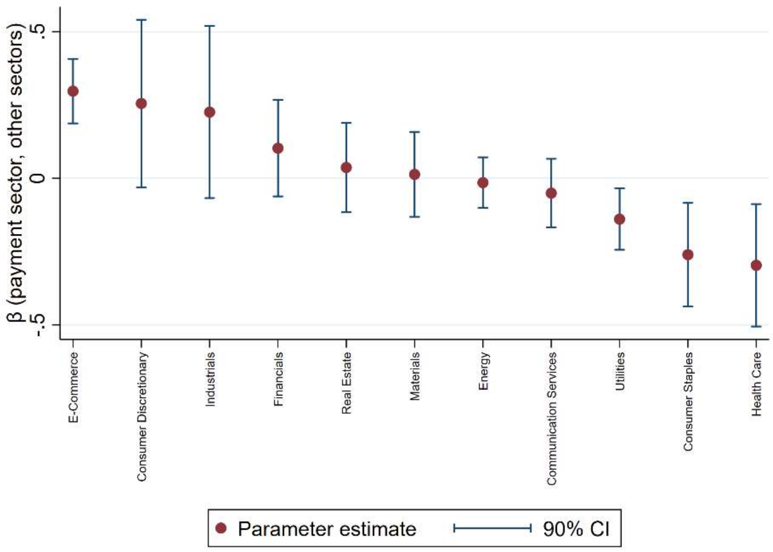


Figure 3: Co-movement of payment firms' stock returns with other sectors

In Panel A, this figure shows the sensitivity of payment sector excess returns to excess return from S&P 500 sector indices and an E-Commerce index. In Panel B, this figure shows the sensitivity of financial sector excess returns (which does not include payment firms) to excess return from S&P 500 sector indices and an E-Commerce index. Excess returns are defined as total returns of the index minus total return of the S&P 500. For the payment index, we use the monthly value-weighted return of payment firms, where payment firms are defined via the SIC code and the business description, see Section 2.1. For the financial index, we use the S&P 500 sector index *Financials*. For E-Commerce, we use the *Dow Jones Internet Commerce Index*. The sample period is from 2004 (the first year where data for the E-Commerce index is available) to 2021.

Panel A: Payment sector



Panel B: Finance sector (ex-payments)

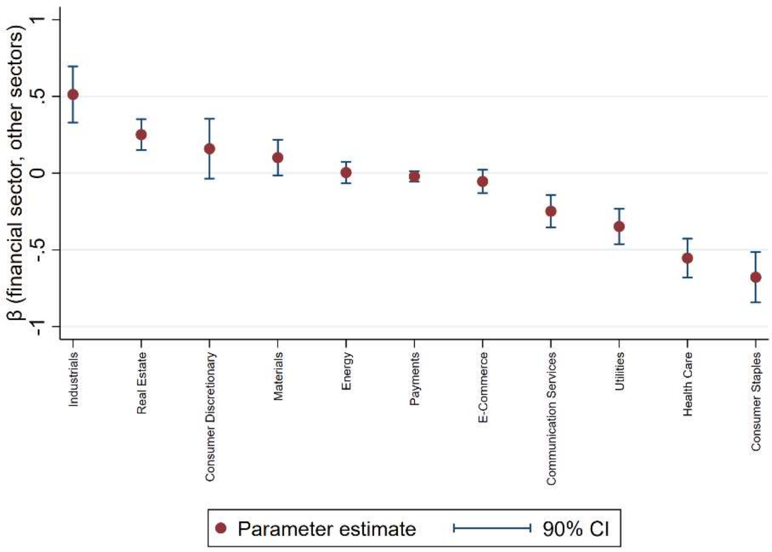


Figure 4: Payment Options Over Time

This figure plots the percentage shares of all payment means in total conversions at the online retailer over time.

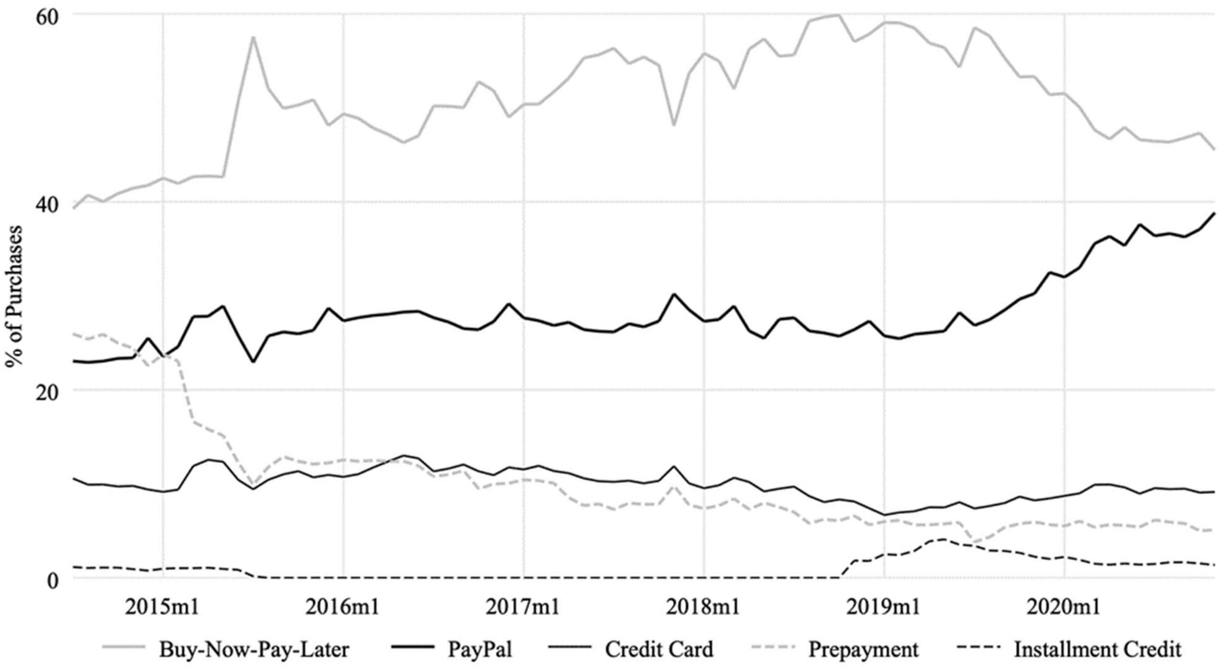


Figure 5: Identity Verification Requirement and Internal Fraud Scores

This figure plots the internal transaction risk scores (higher values imply a greater likelihood of fraud) of all consumers intending to pay by credit card at the final check out website. Smaller black dots are customers required to verify their identity by "3-D Secure" or "Verify by Visa". Larger gray dots represent customers who are not required to go through this process.

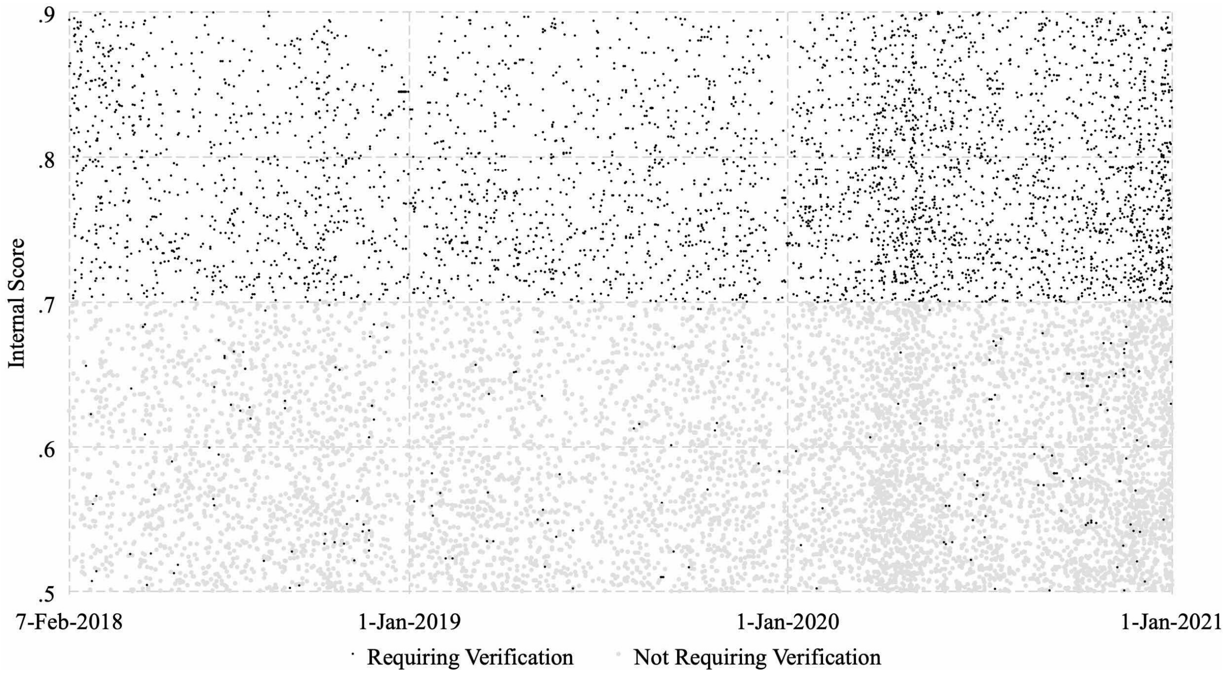
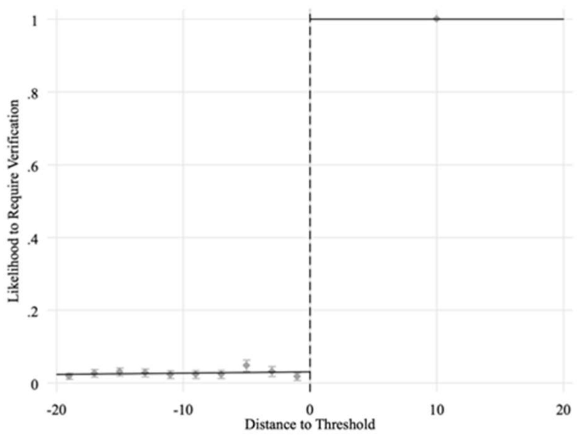
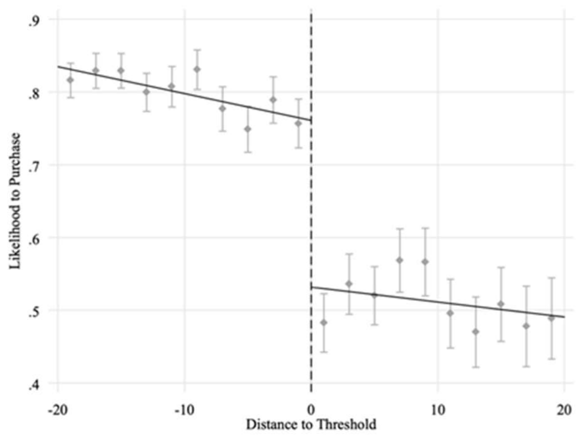


Figure 6: Identity Verification Requirement around the Score Threshold

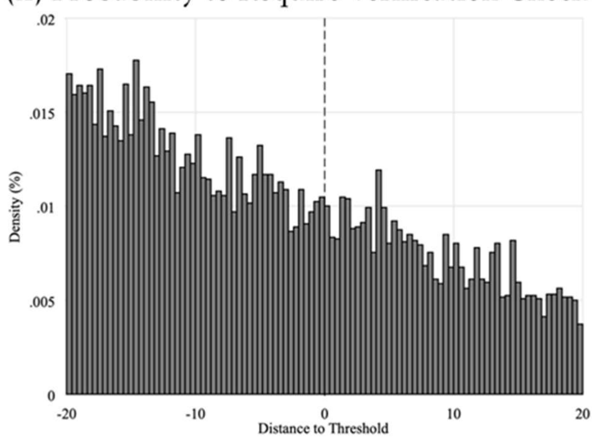
Panel A plots the probability that a customer intending to pay by credit card is required to verify the identity via “3-D Secure” or “Verify by Visa” (vertical axis) against the forcing variable (horizontal axis). The latter is the absolute (score-point) distance from an internal transaction risk score (higher values imply a greater likelihood of fraud). Note that the forcing variable is multiplied with 100 to improve illustration. In panel B the variable on the vertical axis is the likelihood to finalize a purchase (“conversion”). Panel C is a density plot of the forcing variable. Observations to the left (right) of the zero-line in all panels correspond to scores below (above) the score threshold for verification requirement. Each diamond in panels A-B represents the probability within a bin’s width. A bin contains multiple observations. Whiskers are 95% confidence intervals. Black lines are fitted values from regressions on either side of the discontinuity.



(A) Probability to Require Verification Check



(B) Probability of a Successful Conversion



(C) Histogram of Forcing Variable

Figure 7: Hourly Google Searches for Problems with PayPal

This figure plots an index of the average hourly search frequency for problems at PayPal in Germany ("PayPal Störung"). We take extremely high values greater than the 99.5th percentile (illustrated with a red dashed line) as indicators for technical problems in the system or at servers used by PayPal (an "outage"). The majority of hours smaller than the 95th percentile (also illustrated with a red dashed line) are taken as periods without any problems.

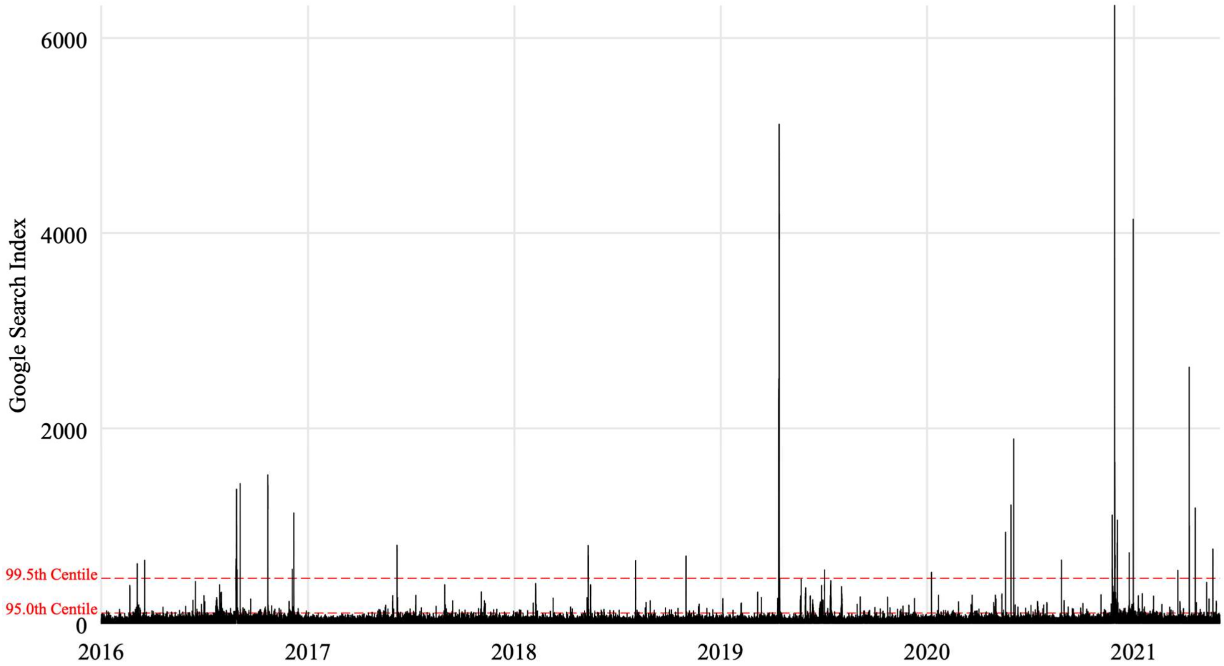


Figure 8: Buy-Now-Pay-Later Offers and Credit Scores

This figure plots external credit scores (higher values imply a lower default likelihood) of all consumers which are offered a Buy-Now-Pay-Later (invoice) payment option from the retailer (meaning they are allowed to pay up to 14 days upon delivery). Smaller black dots represent customers accepting the offer and financing a purchase with it. Larger gray dots are customers not using this offer (they may or may not purchase items). Dates indicate changes in the thresholds used in the lending function of the retailer.

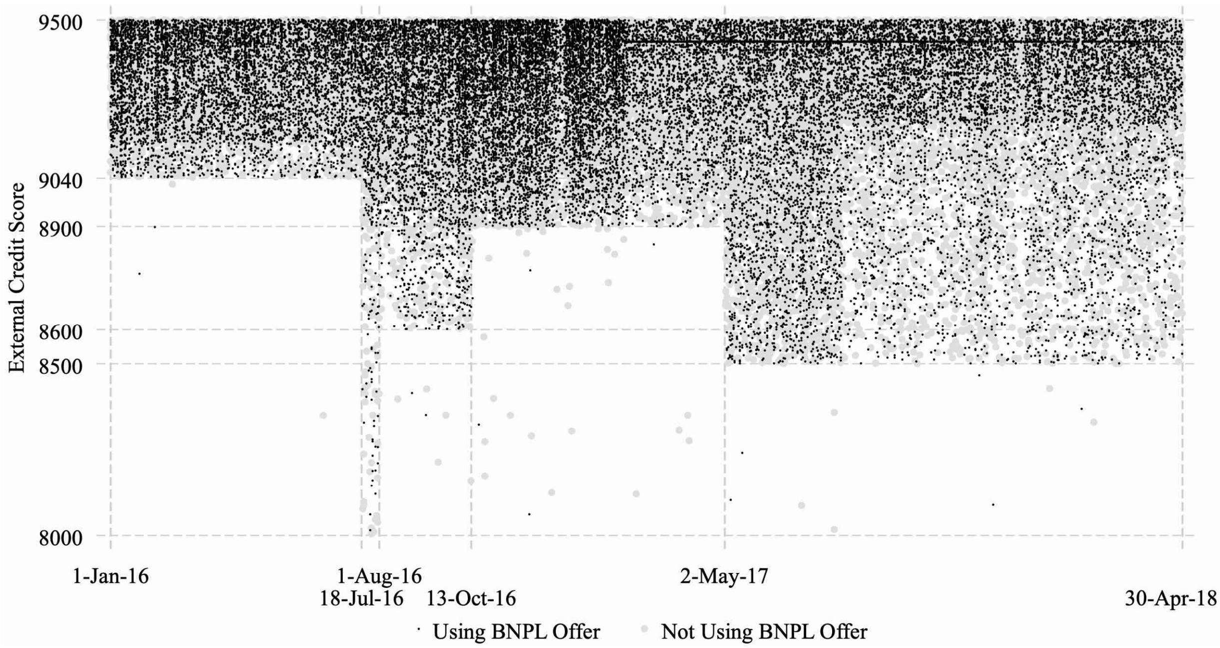
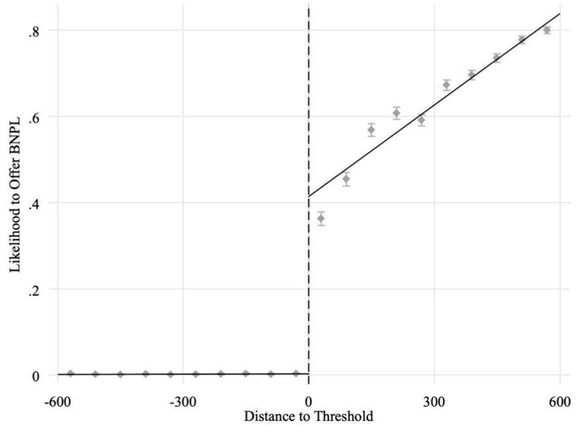
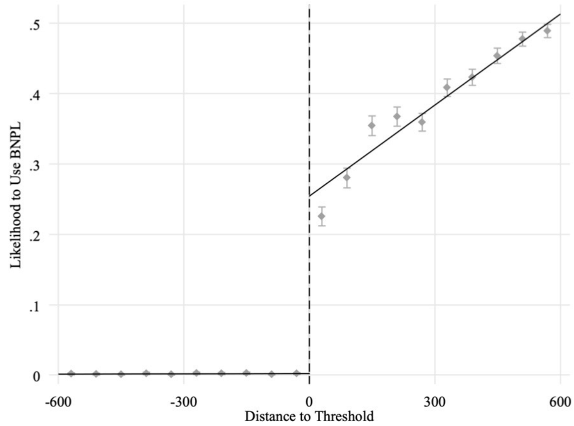


Figure 9: Buy-Now-Pay-Later Offers around the Score Threshold

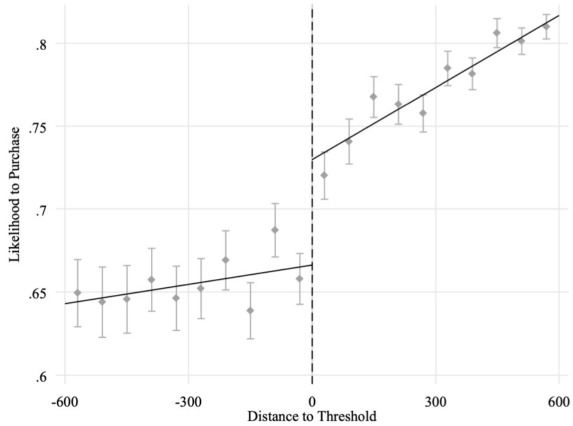
Panel A plots the probability that a potential customer receives a Buy-Now-Pay-Later (invoice) payment offer (vertical axis) against the forcing variable (horizontal axis). The latter is the absolute (score-point) distance from the external credit score threshold (higher credit scores imply a lower default likelihood). In panel B the variable on the vertical axis is the likelihood that a customer uses Buy-Now-Pay-Later. In panel C it is the likelihood to finalize a purchase ("conversion"). Panel D is a density plot of the forcing variable. Observations to the left (right) of the zero-line in all panels correspond to scores below (above) the eligibility threshold. Each diamond in panels A-C represents the probability within a bin's width. A bin contains multiple observations. Whiskers are 95% confidence intervals.



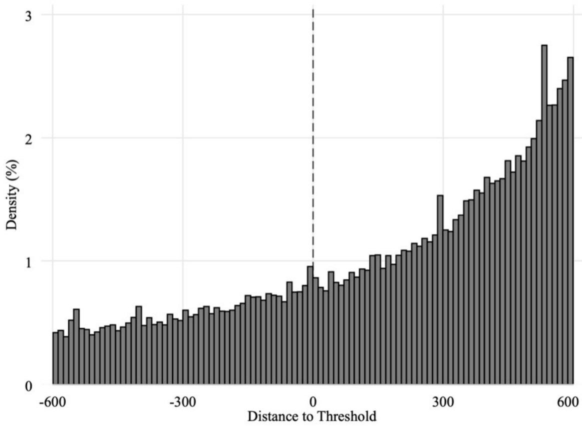
(A) Probability to Offer Buy-Now-Pay-Later



(B) Probability of Using Buy-Now-Pay-Later



(C) Probability of a Successful Conversion



(D) Histogram of Forcing Variable

Black lines are fitted values from regressions on either side of the discontinuity.

Table 1: Largest Firms by Subsector in 2020

This table provides a list of the ten largest firms by market capitalization at year-end 2020 for each of the four finance subsectors. The data is based on U.S. listed firms in 2020 with a SIC-code of 60 (Banks), 61/62 (Brokers, Dealers, Non-Depositary Institutions), 63/64 (Insurance) and Payment Firms. See Section 2.1 and Figure 1 for a detailed definition and description of Payment Firms.

Rank	Payment Firms	Banks	Brokers, Dealers, Non-Dep. Institutions	Insurance
1	Visa	JP Morgan	Morgan Stanley	United Health
	(465bn)	(387bn)	(124bn)	(332bn)
2	Mastercard	Bank of America	Blackrock	Anthem
	(355bn)	(262bn)	(110bn)	(79bn)
3	PayPal	Citigroup	Charles Schwab	Cigna
	(275bn)	(128bn)	(100bn)	(74bn)
4	Square	Wells Fargo	Goldman	Marsh & McLennan
	(99bn)	(125bn)	(95bn)	(59bn)
5	American Express	US Bancorp	CME	Progressive Corp
	(97bn)	(70bn)	(65bn)	(58bn)
6	FIS	Truist	ICE	Humana
	(88bn)	(65bn)	(65bn)	(53bn)
7	Fiserv	PNC	Capital One	Metlife
	(76bn)	(63bn)	(45bn)	(42bn)
8	Global Payments	BNYM	Blackstone	Travelers
	(64bn)	(38bn)	(44bn)	(35bn)
9	Discover	State Street	MSCI	Centene
	(28bn)	(26bn)	(37bn)	(35bn)
10	Fleetcor	First Republic	T. Rowe Price	Verisk
	(23bn)	(26bn)	(35bn)	(34bn)

Table 2: Stock Returns

This table depicts factor loadings for an index of payment firms (Panel A) and an index of financial firms (Panel B). In Panel A, the dependent variable is the monthly value-weighted excess return (return in excess of the one-month U.S. Treasury bill rate) of payment firms. Payment firms are defined via the SIC code and the business description, see Section 2.1. In Panel B, the dependent variable is the monthly excess return of the S&P Financial index. This index includes financials but does not include payment firms. The factor loadings are determined in a Fama-French five-factor model which is augmented using an *E-Commerce minus Brick-and-Mortar (EMB_t)* factor. EMB_t is the return on the Dow Jones E-Commerce index (available since 2004) minus the return on the S&P 500 consumer sectors (average between S&P Consumer Discretionary and S&P Consumer Staples). Column (3) excludes the financial crisis years (2008/2009), column (4) excludes the Corona episode (2020/2021), column (5) refines the Brick-and-Mortar returns using only the industries *Food & Staples Retailing*, *Multiline Retail*, *Specialty Retail*, and *Hotel, Restaurants & Leisure*. The sample period is from 2004-2021, all returns are monthly returns.

Panel A: Payment sector

	(1)	(2)	(3)	(4)	(5)
	2004-2021	2004-2021	exclude 2008/2009	exclude 2020/2021	Refined Brick-and-Mortar
E-Commerce minus Brick-and-Mortar (EMB)		0.244***	0.157***	0.247***	0.162***
		(4.255)	(2.761)	(4.298)	(2.821)
Market	1.136***	1.075***	1.038***	1.081***	1.099***
	(19.66)	(18.75)	(17.52)	(17.37)	(18.82)
SMB	-0.0775	-0.144	-0.127	-0.165*	-0.0951
	(-0.750)	(-1.428)	(-1.239)	(-1.665)	(-0.934)
HML	-0.0550	0.00431	-0.0564	-0.0164	-0.00997
	(-0.590)	(0.0476)	(-0.603)	(-0.164)	(-0.107)
RMW	-0.0221	0.206	0.0683	0.351**	0.143
	(-0.168)	(1.502)	(0.487)	(2.286)	(1.007)
CMA	-0.349**	-0.142	-0.286*	-0.0133	-0.226
	(-2.130)	(-0.862)	(-1.769)	(-0.0775)	(-1.350)
Constant	0.275	0.145	0.163	0.255	0.185
	(1.200)	(0.651)	(0.764)	(1.198)	(0.814)
Observations	216	216	192	192	216
Adj R^2	0.695	0.718	0.688	0.729	0.705

Panel B: Financials (ex-Payment-Sector)

	(1)	(2)	(3)	(4)	(5)
	2004-2020	2004-2020	exclude 2008/2009	exclude 2020/2021	Refined Brick-and-Mortar
E-Commerce minus Brick-and-Mortar (EMB)		-0.0733**	-0.0628**	-0.0678	-0.105***
		(-1.980)	(-2.023)	(-1.622)	(-2.930)
Market	1.159***	1.177***	1.103***	1.189***	1.184***
	(32.08)	(31.79)	(34.05)	(26.22)	(32.47)
SMB	-0.369***	-0.349***	-0.236***	-0.342***	-0.357***
	(-5.708)	(-5.373)	(-4.214)	(-4.748)	(-5.619)
HML	1.076***	1.058***	0.837***	1.125***	1.047***
	(18.48)	(18.08)	(16.36)	(15.44)	(18.03)
RMW	-0.542***	-0.611***	-0.492***	-0.573***	-0.649***
	(-6.594)	(-6.886)	(-6.418)	(-5.126)	(-7.324)
CMA	-0.545***	-0.607***	-0.459***	-0.642***	-0.625***
	(-5.318)	(-5.700)	(-5.203)	(-5.130)	(-5.992)
Constant	-0.313**	-0.274*	-0.173	-0.340**	-0.255*
	(-2.186)	(-1.908)	(-1.479)	(-2.189)	(-1.795)
Observations	216	216	192	192	216
Adj R^2	0.906	0.907	0.908	0.897	0.909

Table 3: The Effect of Credit Card Identity Verification Requirement on Conversions

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer requires a customer who intends to pay with a credit card to go through the "3-D Secure" or "Verify by Visa" process (0 if no verification is required for such customers). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function. Standard errors are clustered by fraud score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
Requiring Verification (1/0)	-0.248***	-0.250***	-0.257***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	25,258	22,405	27,309
Observations	14,477	14,474	14,446

Table 4: The Effect of PayPal Outages on Conversions

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if hourly Google search requests for problems using PayPal are above the 99.5th percentile in the distribution and 0 if the share is below the 95th percentile (those in between are excluded), indicating problems at PayPal. Standard errors are clustered by hour. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Outage (1/0)	-0.061***	-0.046***	-0.033***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
R^2	0.00	0.07	0.08
Observations	2,818,650	2,818,644	2,803,265

Table 5: The Effect of Buy-Now-Pay-Later Offers on Conversions

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer offers Buy-Now-Pay-Later (invoice) as a payment option (0 if this is not offered). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function. Standard errors are clustered by credit score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
BNPL Offer (1/0)	0.152**	0.171**	0.165**
	(0.013)	(0.047)	(0.042)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	38	60	60
Observations	14,418	14,411	14,320

APPENDIX

Figure A.1: Payment Options

This figure plots the percentage shares of all payment means in total conversions at the online retailer for the entire period for which we have data.

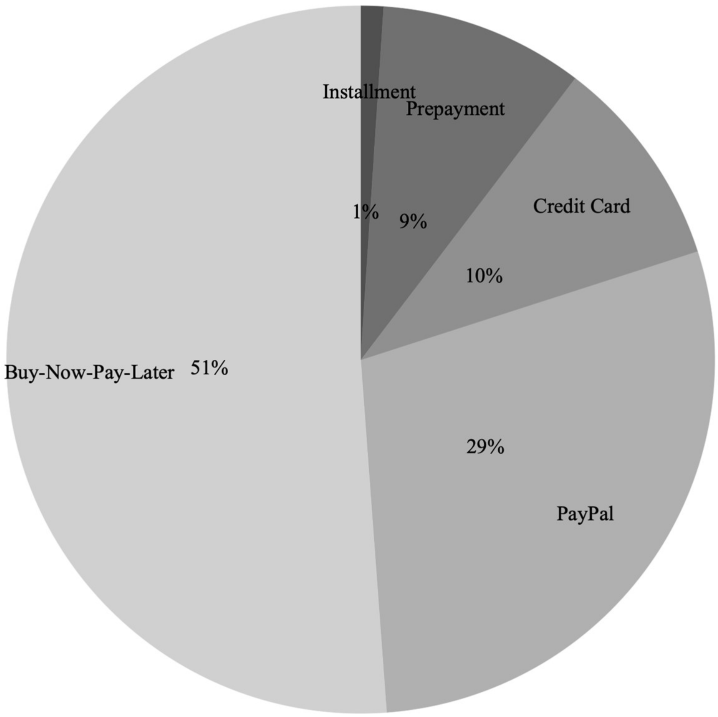


Figure A.2: Payment Options Over Time

This figure plots the absolute number of all payment means used at the online retailer over time.

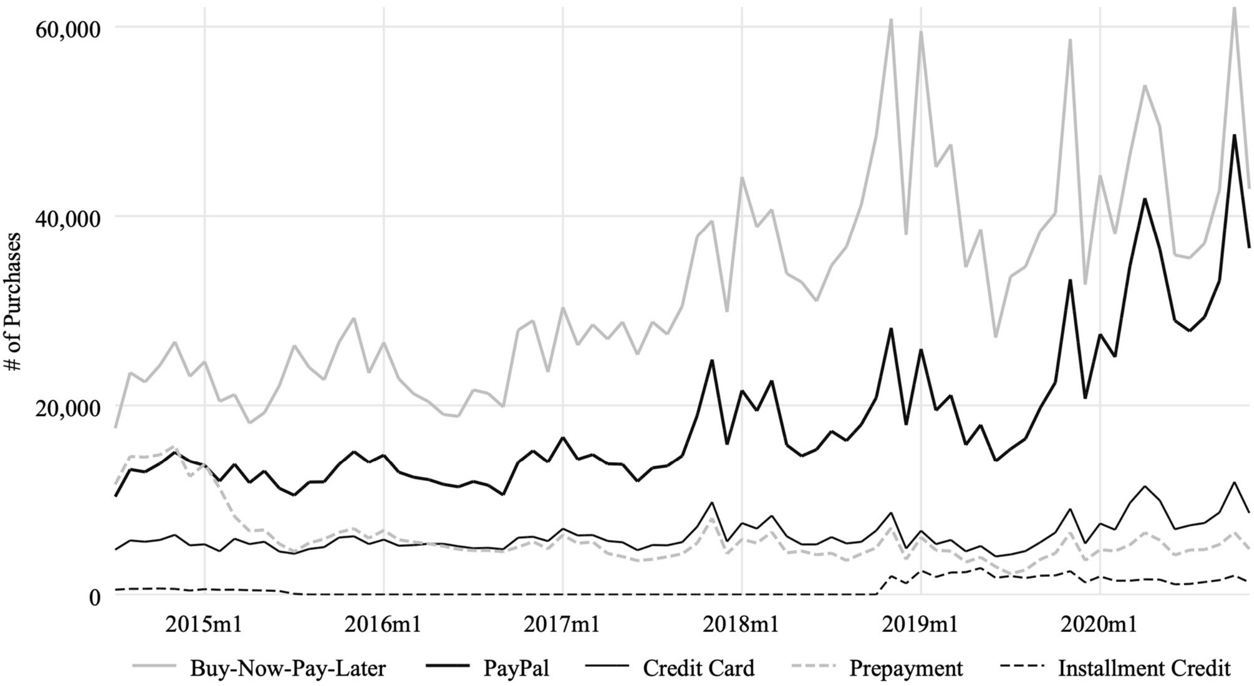


Figure A.3: Hourly Shares of PayPal in Total Conversions

This figure plots the average hourly percentage share of PayPal in all transactions at the online retailer over time.

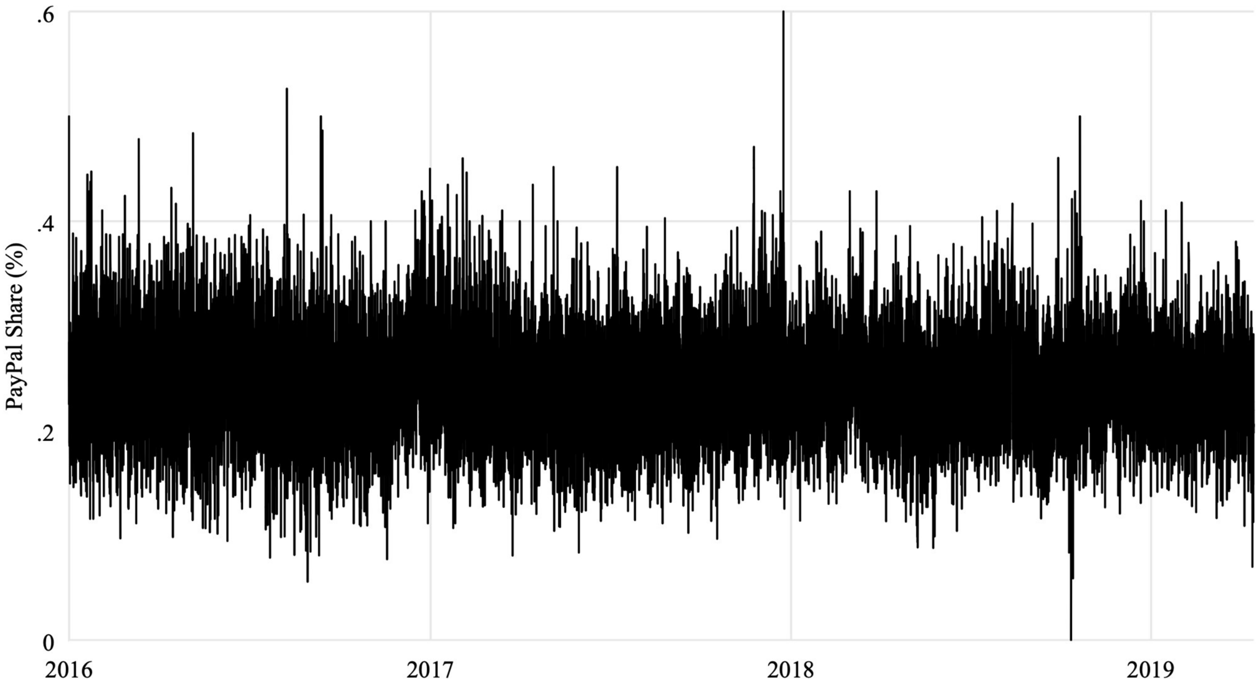
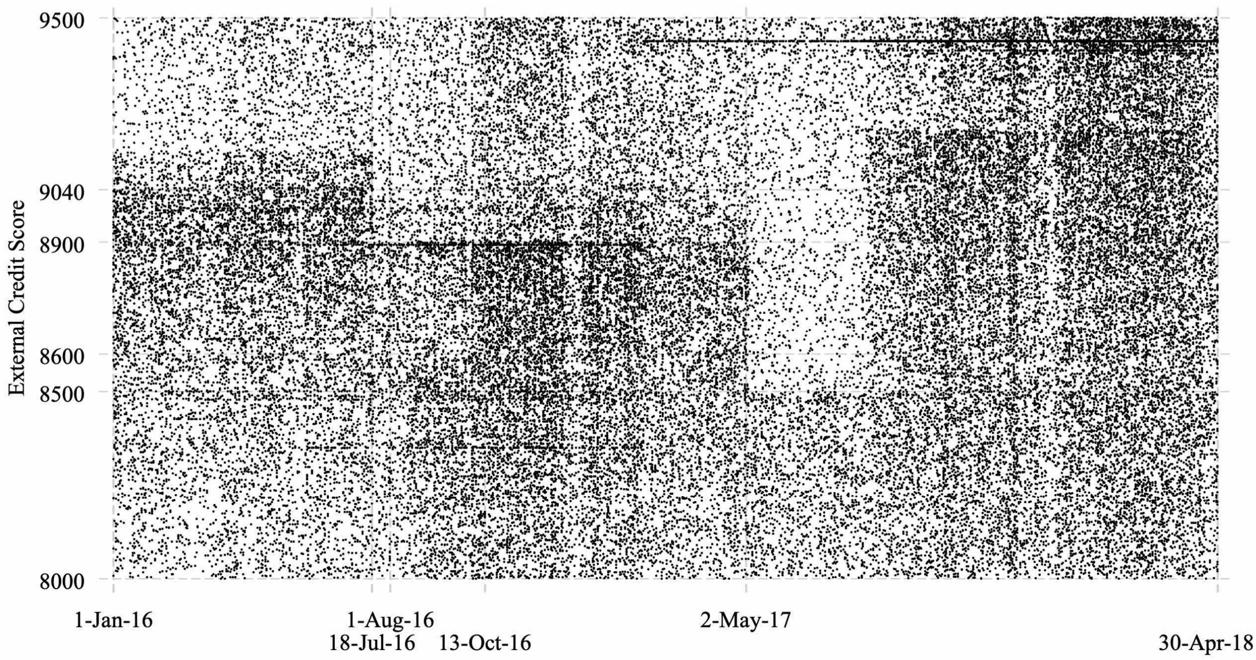


Figure A.4: Buy-Now-Pay-Later Offers and Credit Scores

This figure plots external credit scores (higher values imply a lower default likelihood) of all consumers which are *not* offered any Buy-Now-Pay-Later (invoice) payment option from the retailer (meaning they are allowed to pay up to 14 days upon delivery). Dates indicate changes in the thresholds used in the lending function of the retailer.



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: The acquirer, typically a bank, 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 acquirer 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 issuer, including authorization (for example, checking AML 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).

FinTechs like PayPal, Square (now named Block), and Adyen have carved out part of the acquirer value chain; while 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 fraught on the merchant side – the acquirer must refund the cardholder.

Table A.1: Payment Value Chain

	Merchant	Acquirer	Network	Issuing Bank	Cardholder
Key function	Sells goods/services	• POS-terminal (in-store) / Payment gateway (E-Commerce) • Acquirer Processing[23] • Merchant Bank Account	• Rules/Standards • Network Processing[1]	• Issuer Processing[1] • Cardholder Bank Account	Buys goods/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[24]	None	Credit and fraud risk for transactions that are verified via the issuing bank (PIN, or 3D-secure)	None (Exception: gross negligence)
Fees	Receives product price minus acquirer markup, scheme fees, and interchange fee	Acquirer Markup	Scheme Fees	Interchange Fee	Pays product price
Fee amount	50-350 bps depending on payment method and location	Ø worldwide (latest): FIS: 13bps Adyen: 22bps PayPal: 146 bps[25] Square: 125 bps[3]	Ø worldwide (latest): Visa: 19bps Mastercard: 23bps Amex and Discover are not comparable[26]	Ø US and Europe (latest):[27] US Debit: 73bps US Credit: 174bps Europe Debit: 20bps Europe Credit: 30bps	Not applicable
Examples	Walmart, Target, Wayfair, Etsy	Various banks; POS-Terminal: Ingenico, Verifone; Gateway: PayPal, Square; Acquirer processing: FIS, Chase Paymentech, Global Payments, Adyen	Visa, Mastercard	Bank of America, Citigroup, Bank of America, Wells Fargo Other parts of the value chain: Apple Pay, Google Pay[28]	Jane Doe, John Doe

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

[24] 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 (for example, 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.

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

[26] American Express and Discover acts as acquirer, network, and issuer. American Express, for example, earned 36.1bn in revenue in 2020, equivalent to 361bps of their payment volume of 1.0trn.

[27] In the U.S., debit card interchange fees are limited by the Durbin amendment, applicable to banks with over 10bn in assets, to 21 cent + 5 basis point of the transaction (plus 1 basis point for fraud-prevention measures). In Europe, consumer debit card fees are capped at 20bps, consumer credit card fees at 30bps.

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

Table A.2: Variable Definitions

Variable	Definition
Dependent Variable	
Conversion (1/0)	equal to 1 if a visit of the check out website is converted to a purchase
Treatments	
Buy-Now-Pay-Later (1/0)	equal to 1 if Buy-Now-Pay-Later / invoice is offered as a payment option
Requiring Verification (1/0)	equal to 1 if the retailer requires additional identity verification via "3-D Secure" or "Verify by Visa"
PayPal Outage (1/0)	equal to 1 if the hour is in the top 99.5th percentile of Google searches for problems at PayPal in Germany ("PayPal Störung") or and equal to 0 if it is below the 95th percentile (observations in between are excluded)
Credit Scores	
External Credit Score	numeric external credit score of the potential customer (from a German private credit bureau); ranging from 0 (worst) to 10,000 (best); the numeric value and 100 1-percentile bins are used in regressions
Internal Fraud Score	numeric internal fraud score computed from the potential customer's digital footprint; ranging from 0 (worst) to 1 (best); the numeric value and 100 1-percentile bins are used in regressions
Customer Characteristics (Controls and Fixed Effects)	
Male (1/0)	dummy variable identifying the (binary) gender of the potential customer
Age	age of customer in years; used in regressions in logarithm
County	403 counties ("Landkreise und kreisfreie Städte")
Website Visit Characteristics (Controls and Fixed Effects)	
Shopping Cart Value	value of the shopping cart in €; the numeric value and 50-€FE bins are used in regressions
Week	calendar weeks of check-out, from the first week of 2016 to the last week of April, 2018)
Day-of-week	dummy vector for week day of the check-out (1-7)
Time-of-day	dummy vector for time at check-out, morning (after 5 am to 12 pm), day (12 pm to 6 pm), evening (after 6 pm to 10 pm), night (after 10 pm to 5 am)
Device	dummy vector for device used to access the website (desktop, tablet, or phone)
Operating System	dummy vector for operating system used to access the website (Mac OS or iOS, Windows, or Android)

Table A.3: Descriptive Statistics – Credit Card

Observations come from regression 1 in table 4. See table A1 for details on the definition of variables. Apple includes Macintosh and iOS systems.

	N	10th Perc.	Median	90th Perc.	Mean	SD
Conversion (1/0)	14,477	0	1	1	.704	.457
Fraud Score Customer	14,477	.5	.632	.838	.651	.124
Distance to Threshold	14,477	-2	-.677	1.38	-.488	1.24
Above Threshold (1/0)	14,477	0	0	1	.342	.475
Verification Required (1/0)	14,477	0	0	1	.359	.48
Cart Value (Euro)	14,477	63	350	1,500	590.2	613.7
Male (1/0)	14,474	0	1	1	.572	.495
Time - Morning (1/0)	14,477	0	0	1	.251	.434
Time - Day (1/0)	14,477	0	0	1	.37	.483
Time - Evening (1/0)	14,477	0	0	1	.336	.472
Time - Night (1/0)	14,477	0	0	0	.043	.202
Device - Computer (1/0)	14,474	0	1	1	.871	.335
Device - Phone (1/0)	14,474	0	0	1	.108	.311
Device - Tablet (1/0)	14,474	0	0	0	.02	.141
System - Apple (1/0)	14,474	0	0	1	.294	.456
System - Windows (1/0)	14,474	0	1	1	.542	.498
System - Android (1/0)	14,474	0	0	0	.064	.245

Table A.4: Descriptive Statistics – PayPal

Observations come from regression 1 in table 5. See table A1 for details on the definition of variables. Apple includes Macintosh and iOS systems. We use age fixed effects and include a separate fixed effect for missing age information to analyze more observations.

	N	10th Perc.	Median	90th Perc.	Mean	SD
Conversion (1/0)	2,818,650	0	1	1	.763	.425
PayPal Outage (1/0)	2,818,650	0	0	0	.003	.058
Cart Value (Euro)	2,818,650	55	210	800	340	364
Male (1/0)	2,818,648	0	0	1	.375	.484
Age	2,055,930	26	40	61	42.2	13.4
Time - Morning (1/0)	2,818,650	0	0	1	.209	.407
Time - Day (1/0)	2,818,650	0	0	1	.36	.48
Time - Evening (1/0)	2,818,650	0	0	1	.397	.489
Time - Night (1/0)	2,818,650	0	0	0	.033	.179
Device - Computer (1/0)	2,818,648	0	1	1	.569	.495
Device - Phone (1/0)	2,818,648	0	0	1	.291	.454
Device - Tablet (1/0)	2,818,648	0	0	1	.139	.346
System - Apple (1/0)	2,818,648	0	0	1	.32	.467
System - Windows (1/0)	2,818,648	0	0	1	.367	.482
System - Android (1/0)	2,818,648	0	0	1	.191	.393

Table A.5: Descriptive Statistics – Buy-Now-Pay-Later

Observations come from regression 1 in table 6. See table A1 for details on the definition of variables. Apple includes Macintosh and iOS systems. We use age fixed effects and include a separate fixed effect for missing age information to analyze more observations in regressions.

	N	10th Perc.	Median	90th Perc.	Mean	SD
Conversion (1/0)	14,418	0	1	1	.703	.457
Credit Score Customer	14,418	8,458	8,854	9,077	8,784	238
Credit Score Threshold	14,418	8,500	8,900	9,040	8,780	227
Distance to Threshold	14,418	-95	4	100	4.164	69.988
Above Threshold (1/0)	14,418	0	1	1	.518	.5
BNPL Offered (1/0)	14,418	0	0	1	.215	.411
Cart Value (Euro)	14,418	74	270	870	384.9	370.5
Male (1/0)	14,418	0	0	1	.378	.485
Age	6,902	22	32	51	34.6	11
Time - Morning (1/0)	14,418	0	0	1	.193	.395
Time - Day (1/0)	14,418	0	0	1	.357	.479
Time - Evening (1/0)	14,418	0	0	1	.411	.492
Time - Night (1/0)	14,418	0	0	0	.038	.192
Device - Computer (1/0)	14,418	0	1	1	.606	.489
Device - Phone (1/0)	14,418	0	0	1	.267	.443
Device - Tablet (1/0)	14,418	0	0	1	.127	.333
System - Apple (1/0)	14,418	0	0	1	.302	.459
System - Windows (1/0)	14,418	0	0	1	.397	.489
System - Android (1/0)	14,418	0	0	1	.163	.369

Table A.6: The Effect of Identity Verification Requirement on Conversions – 10% Wider Bandwidth

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer requires a customer who intends to pay with a credit card to go through the "3-D Secure" or "Verify by Visa" process (0 if no verification is required for such customers). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function (and widened by 10%). Standard errors are clustered by fraud score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parenthesis.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
Requiring Verification (1/0)	-0.248***	-0.252***	-0.260***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	25,378	23,695	32,714
Observations	16,043	16,038	16,005

Table A.7: The Effect of Identity Verification Requirement on Conversions – 10% Narrower Bandwidth

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer requires a customer who intends to pay with a credit card to go through the "3-D Secure" or "Verify by Visa" process (0 if no verification is required for such customers). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function (and narrowed by 10%). Standard errors are clustered by fraud score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parenthesis.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
Requiring Verification (1/0)	-0.242***	-0.239***	-0.248***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	20,444	16,753	22,620
Observations	12,910	12,907	12,879

Table A.8: The Effect of PayPal Outages on Conversions – Using Higher Hourly Search Frequencies

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if hourly Google search requests for problems using PayPal are above the 99.9th percentile in the distribution and 0 if the share is below the 95th percentile (those in between are excluded), indicating problems at PayPal. Standard errors are clustered by hour. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Outage (1/0)	-0.117***	-0.076***	-0.044***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
R^2	0.00	0.07	0.08
Observations	2,812,745	2,812,739	2,797,392

Table A.9: The Effect of PayPal Outages on Conversions – Using Lower Hourly Search Frequencies

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if hourly Google search requests for problems using PayPal are above the 99th percentile in the distribution and 0 if the share is below the 95th percentile (those in between are excluded), indicating problems at PayPal. Standard errors are clustered by hour. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Outage (1/0)	-0.047***	-0.037***	-0.027***
	(0.000)	(0.000)	(0.000)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
R^2	0.00	0.07	0.08
Observations	2,827,439	2,827,433	2,812,015

Table A.10: The Effect of PayPal Outages on Conversions – Using Low Hourly PayPal Shares

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if hourly %-shares of customers using PayPal at the retailer is below the 0.5th percentile in the distribution of hours and 0 if the share is above the 5th percentile (those in between are excluded, as are those hours with less than 50 conversions), indicating problems at PayPal. Standard errors are clustered by hour. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Outage (1/0)	-0.029**	-0.033***	-0.020**
	(0.036)	(0.006)	(0.047)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
R^2	0.00	0.07	0.08
Observations	2,579,671	2,579,664	2,565,968

Table A.11: The Effect of Buy-Now-Pay-Later Offers on Conversions – 10% Wider Bandwidth

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer offers Buy-Now-Pay-Later (invoice) as a payment option (0 if this is not offered). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function (and widened by 10%). Standard errors are clustered by credit score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parenthesis.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
BNPL Offer (1/0)	0.120*	0.145*	0.133*
	(0.067)	(0.094)	(0.094)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	33	54	52
Observations	15,831	15,824	15,730

Table A.12: The Effect of Buy-Now-Pay-Later Offers on Conversions – 10% Narrowed Bandwidth

Regressions in this table explain the likelihood that a customer's shopping visit at the retailer's website is converted into a purchase. Results are linear probability estimates. The independent variable of interest is a dummy equal to 1 if the retailer offers Buy-Now-Pay-Later (invoice) as a payment option (0 if this is not offered). All estimates come from a fuzzy RDD, implemented via 2SLS. The optimal bandwidth is selected with a triangular kernel function (and narrowed by 10%). Standard errors are clustered by credit score bin (grouped by 100 percentiles). ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parenthesis.

Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
BNPL Offer (1/0)	0.153***	0.175**	0.163**
	(0.009)	(0.037)	(0.033)
Controls			
Customer		Yes	Yes
Website Visit		Yes	Yes
Fixed Effects			
County			Yes
Week			Yes
Day-of-Week			Yes
Time-of-Day			Yes
Kleibergen-Paap Robust F-Stat	52	87	78
Observations	12,977	12,969	12,883