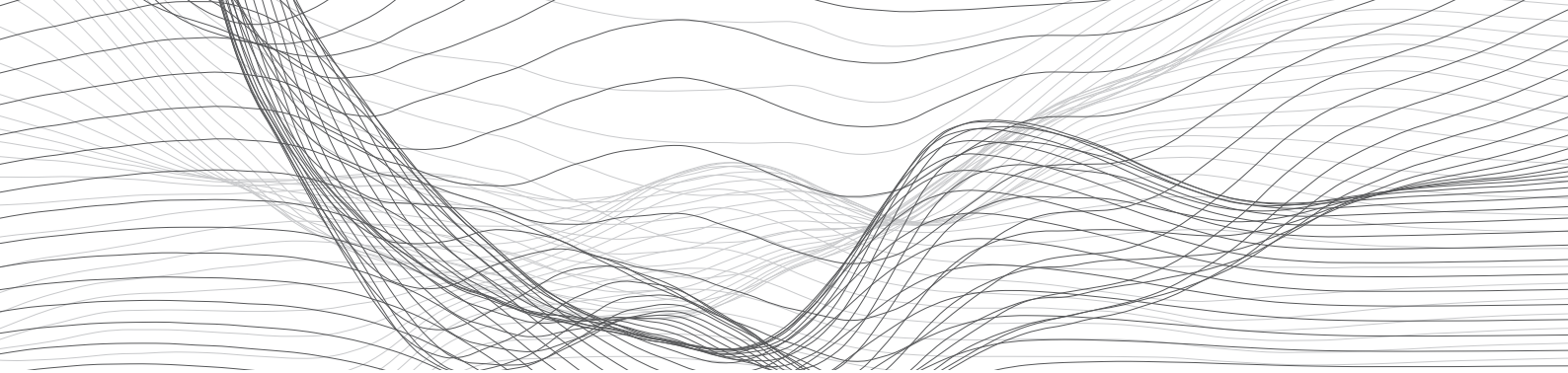




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Cash saves the day: How cash infrastructure enhances resilience during a card payment system outage

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Abstract

Can cash infrastructure mitigate the adverse effects of a card payment system outage? As cashless payment systems become increasingly prevalent, societies are becoming more vulnerable to technical disruptions such as card payment system outages. This paper investigates a one-day nationwide card payment system outage at a major retailer in Switzerland. To quantify the loss in card sales at the retailer's stores and the increase in cash withdrawals at ATMs, we generate granular counterfactuals by forecasting card payments and cash withdrawals at the store and ATM level. We then use residual-on-residual regressions to control for high-dimensional confounders and estimate the causal effect of outage-induced card payment losses on ATM withdrawals in an event-study framework. Our district-level results suggest that for every 100 lost card payments, there were 11 additional ATM withdrawals. In value terms, for every CHF 100 loss in card payments, ATM withdrawals increased by approximately CHF 68. We also find only limited evidence of increased card payments at competing stores during the outage or at outage-affected stores on the day after the outage. Our findings suggest that cash infrastructure can serve as a resilience buffer during card payment system outages and that consumers rely on cash as their primary fallback payment instrument.

Keywords: Card payments, ATM withdrawals, resilience, payment system risk, forecasting

JEL Codes: C55, D12, E42, G28

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1 Introduction

Reliable cashless payment systems are essential to the functioning of modern economies. With the rapid adoption of debit cards, credit cards, and mobile payments, technical disruptions at the point of sale have become increasingly costly. In Switzerland alone, the cashless share of point-of-sale transactions rose from 28% in 2017 to 70% in 2024 (Swiss National Bank [SNB], 2018, 2025b), yet more than half of survey respondents reported having experienced a payment disruption in the past 12 months (SNB, 2025b). Anecdotal evidence underscores the potential scale of technical disruptions. A 2018 Visa outage across Europe led to 5 million failed transactions (Hogg, 2018), while the 15-hour Rogers telecommunications outage in Canada—which also affected card payments—inflicted an estimated \$142 million in economic losses (Gannon, 2023).

Public institutions recognize the risks posed by technical disruptions and invest in the design of resilient payment systems (Aboulaiz et al., 2024; Khiaonarong et al., 2021). In Switzerland, banks, payment service providers, and retail merchants — coordinated by federal agencies — recently agreed to introduce offline payment capabilities for credit and debit cards (Federal Office for National Economic Supply, 2026). In other countries, central banks are developing retail central bank digital currencies with offline capabilities (Minwalla et al., 2023). Cash, however, remains a highly resilient payment system and is particularly sought after during crises (Rösl & Seitz, 2022). Despite having one of the lowest cash usage rates in Europe, Sweden actively maintains its cash infrastructure to preserve resilience in times of crisis or war (Sveriges Riksbank, 2025). More broadly, governments and regulators across Europe are taking steps to safeguard cash access: the European Commission (European Commission, 2023) has proposed measures to ensure that citizens and businesses retain access to cash, the Netherlands’ proposed Cash Payments Act aims to guarantee a minimum level of cash services (Ministerie van Financiën, 2023), and the United Kingdom’s Financial Services and Markets Act 2023 grants regulators new powers to safeguard cash access (House of Commons Treasury Committee, 2025). Finland, Hungary, Ireland, and Spain have similar legislative and regulatory initiatives in place or under development (OECD, 2025). However, despite growing attention to resilient payment system design, little is known about the costs of card payment system outages and how consumers respond to them, including the extent to which cash serves as a fallback during such events.

In this paper, we investigate the costs of and consumer reactions to a nationwide card payment system outage at a large Swiss retailer in 2022. For almost an entire business day, the retailer’s card payment system failed across all approximately 2,400 of its stores, preventing almost all card payments. Faced with this outage, consumers could react in several ways: paying with cash on hand, withdrawing cash from a nearby ATM or bank branch and returning to the affected store, switching to a competing retailer with a functioning payment system, delaying their purchase, or forgoing the purchase altogether. Evidence from the 2022 payment method survey suggests that cash is an important fallback in such situations—55% of respondents re-

ported having used cash when encountering a technical disruption (SNB, 2023).

To causally identify and quantify the relative importance of these consumer reaction channels, we rely on granular card payment and ATM withdrawal forecasts. We first construct forecasts of card payments for all Swiss retail stores and cash withdrawals for all ATMs in Switzerland, based on anonymized single-transaction data. Comparing these forecasts to observed card payments allows us to identify which stores experienced an outage and to quantify their loss in card payments. Positive residuals in ATM withdrawals indicate whether consumers reacted by withdrawing excess cash. Furthermore, we test whether outage-affected stores experienced more card payments than expected on the day following the outage. We use propensity score matching to identify stores in the same postal code district with similar transaction patterns and assess whether competing retailers with functioning payment systems experienced increased card sales on the outage day. Following the double-debiased machine learning literature (Chernozhukov et al., 2018), we use a residual-on-residual regression at the district level to control for high-dimensional confounders. Treating the outage as a random shock in an event-study framework, we estimate the causal effect of outage intensity—measured by the loss in card payments—on the proposed consumer reaction channels. In further specifications, we add controls that capture district characteristics such as ATM density per capita and the baseline cash usage share.

Our results suggest that consumers primarily reacted to the card payment system outage by withdrawing cash, and we find no strong evidence of increased card payments at competing stores or the day after the outage. Using a two-step forecasting pipeline with pretraining and fine-tuning via light gradient boosting machines, we achieve R^2 values above 0.8 for the daily card payment value and volume at the store level and R^2 values above 0.6 for the daily withdrawal value and volume at the ATM level. Based on the resulting residuals, we classify stores with a decrease of more than 1.5 standard deviations in both the card payment value and volume as affected by the outage. We identify approximately 2,250 such stores, which experienced a combined loss of roughly 700,000 card payments totaling CHF 22 million. On the same day, there was an excess of approximately 85,000 ATM withdrawals worth CHF 20 million. Our residual-on-residual regression suggests that 100 lost card payments led to 11 additional ATM withdrawals, equivalent to CHF 68 in additional cash withdrawals per CHF 100 lost in card payments. In specifications with district controls, we find that districts with a higher ATM density—number of ATMs per 1,000 inhabitants—have a higher baseline level of ATM withdrawals on the outage day. For the other consumer reaction channels, we find no strong effects of the outage on card payments at competing stores or at outage-affected stores the day after.

This paper shows that cash infrastructure can enhance resilience in the event of a card payment system outage and that consumers rely on cash as their fallback payment instrument. In the case of a one-day card payment system outage at a large Swiss retailer, we identify a strong causal link between outage intensity—measured by card payment losses—and excess ATM withdrawals. However, we do not find a significant increase in card payments at competing retailers with working card payment systems or the day after the outage. This finding

suggests that consumers primarily responded to the outage by switching to cash rather than to other functioning cashless alternatives. These results underscore the importance of maintaining accessible cash infrastructure as a safeguard against the operational risks of cashless payment systems, allowing it to serve as a resilience buffer during outages. In other outage scenarios, cash infrastructure itself might also be affected; nevertheless, our findings highlight that consumers rely on cash as their primary resilience mechanism over other cashless alternatives.

2 Related literature

There is prior literature on outage detection in interbank payment systems, fraud and security protocols of retail payment systems, and systemic risks of retail payment systems. Several studies have examined methods for detecting outages and evaluating participant behavior in interbank payment systems. For instance, Klee (2010) identifies prolonged periods of unusually low activity in the Fedwire system as indicators of operational outages, estimating how such outages cause deviations from the Federal Reserve’s target interest rate and modeling how participants adjust their behavior in response. Similarly, Glowka et al. (2018) develop an algorithmic method to detect outages in the European TARGET2 system. Arjania and Heijmans (2020) extend this approach and validate it using a documented list of operational incidents in Canada’s interbank payment system. Desai et al. (2025) propose a framework for detecting anomalous payments on a single-transaction basis. However, these studies focus exclusively on interbank payment systems and do not address outages in retail or card payment systems.

A substantial body of literature addresses fraud and security protocols in retail payment systems. Much of this work focuses on credit card fraud detection using modern machine learning techniques, particularly under extreme class imbalances (Bin Sulaiman et al., 2022; Chan et al., 1999; Dal Pozzolo et al., 2017). System engineering research further addresses the design of secure payment systems, including mobile (Ahmed et al., 2021; Bojjagani et al., 2023) and contactless (Onumadu & Abroshan, 2024) payments. While this literature deals with preventing illicit payments, it does not address the systemic risks stemming from operational failures in retail payment systems.

Only a few studies examine outages and systemic risks in retail payment systems. An IMF report highlights how the digitization of payments has increased operational risks, discussing scenarios of large-scale disruptions (Khiaonarong et al., 2022), while Allen (2021) argues that society’s growing dependence on electronic payments requires new regulatory frameworks to mitigate cascading operational failures. The Reserve Bank of Australia has surveyed the frequency of retail payment system outages and has reported that large outages are rare (Griffiths & Joyce, 2024). More recently, the ECB has examined the role of cash during crises, highlighting its critical importance during the April 2025 Iberian blackout, when digital infrastructures failed (Faella & Zamora-Pérez, 2025). Most related to our study is Alvarez et al. (2026), who also use highly granular data from the US to show that natural disasters cause card payment outages, while consumers increase their precautionary cash holdings to counteract the expected

disruptions to card payment systems.

A study from Brazil, on the other hand, focuses on a cash system outage and investigates its effect on payment technology adoption. Mariani et al. (2023) show that customers increase their usage of cashless payments when there is a cash service suspension due to hit-and-run raids performed by criminal groups. Not only does the number of cashless payment transactions increase during the suspension of cash services, but the effect also persists thereafter.

With this paper, we contribute to the growing literature on the effects of retail payment system outages and, to the best of our knowledge, are the first to provide empirical evidence that consumers reacted to an unexpected partial card payment system outage primarily by withdrawing cash at ATMs.

3 Institutional setting

Payments at the point of sale (POS) depend on a chain of interlinked services. In simplified form, this chain includes (1) the retailer's own register and IT system, which scans products, registers purchases, and initiates the payment at the POS terminal; (2) the POS terminal hardware and software, which display the total purchase price and send the payment request to the acquirer; (3) the acquirer or payment service provider, which sends an authorization request over the card scheme to the card issuer and later settles funds with the retailer; (4) the card scheme network, which defines the rules of a payment method and communicates between the acquirer and the card issuer; and (5) the issuer of the payment card, often a bank, which authorizes and books the payment on the customer's credit or debit account.

A disruption to any one of these services can produce very different forms of outages. A problem with the retailer's own register (service 1) typically affects only a specific retailer and its stores. A disruption of the terminal or acquirer (services 2 and 3) affects the set of retailers using the affected software or hardware provider. However, a problem with the scheme or issuer institution (services 4 and 5) affects a large set of payment cards issued or processed by those institutions. Finally, payment disruptions can also be triggered by the failure of the underlying infrastructure on which all payment processing services depend. For instance, an electricity or internet outage renders all services impossible.

In this paper, we investigate a nationwide outage of the register and IT system of one retailer (service 1), which rendered cashless payments at its stores impossible for one day. However, the other services in the chain (services 2–5) remained operational, allowing card payments at other retailers and cash withdrawals at ATMs to continue as normal. In this setting, there are several distinct consumer reaction channels: paying with cash on hand, withdrawing cash at an ATM, switching to a different retailer, delaying their purchase until the following day or forgoing the purchase altogether. Our data allow us to identify withdrawing cash, switching retailers, and delaying the purchase but not the extent to which consumers relied on cash on hand or forwent their purchase. The 2022 payment methods survey shows that more than 90%

Table 1: Summary statistics of daily card payments at stores and ATM withdrawals; Observation period: 2020-2022.

	No. of stores or ATMs	Share of non-zero days	Volume per day		Value per day in CHF	
			median	mean	median	mean
Cards payments	26,956	84.8%	29	97	1,366	4,490
ATM withdrawals	5,628	96.2%	51	61	17,750	24,235

of the population carried cash in their wallets, with a median value of CHF 86 (SNB, 2023).

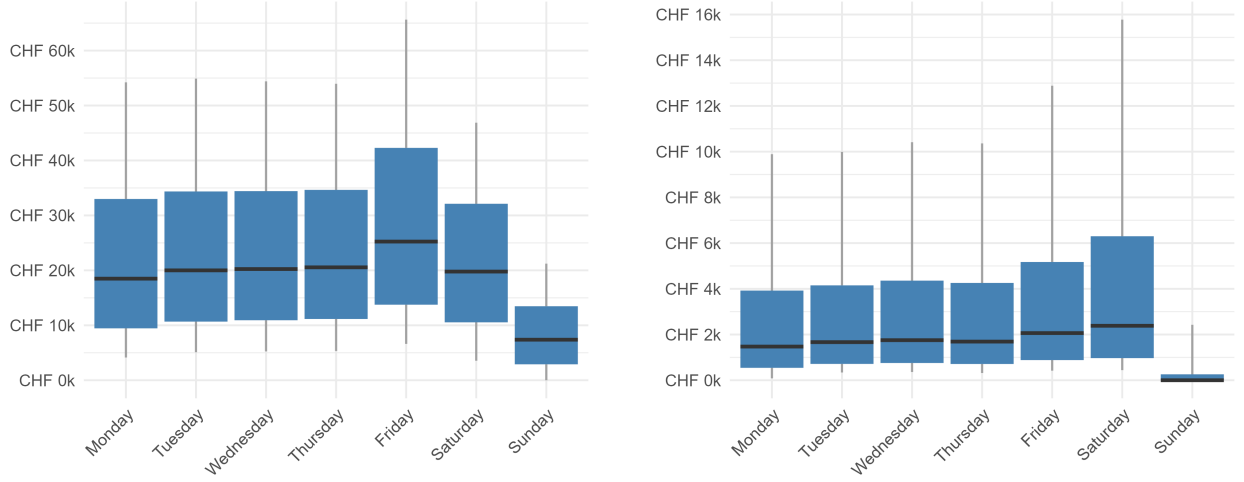
4 Data

In this paper, we use single-transaction data on card payments and ATM withdrawals to estimate the costs of a card payment system outage and to quantify the proposed consumer reaction channels. The data are provided by Swiss payment service providers, namely, Worldline Switzerland Ltd., PostFinance Ltd., and SIX Ltd. During the analysis period, PostFinance and Worldline processed approximately four-fifths of all card payments, whereas PostFinance and SIX together handled almost all ATM transactions in Switzerland.

The datasets include variables such as transaction value, anonymous store and ATM identifiers, the transaction date, and location information—postal codes for stores and districts for ATMs, with postal codes being more geographically granular. We restrict the card payment data to retail trade (NOGA 47 as defined by the Federal Statistical Office, 2022), which includes stores such as supermarkets, clothing stores, and electronics retailers. Table 1 presents summary statistics for daily card payments at retail stores and daily cash withdrawals at ATMs. The data range from 2020 to the end of 2022. The median retail store processed 29 card payments per day totaling CHF 1,366, while the median ATM processed 51 withdrawals worth CHF 17,750. The large difference between the median ATM withdrawal value and the median card payment value reflects the fact that consumers typically withdraw cash to fund multiple purchases across multiple stores. Furthermore, 14% of daily store-level observations record no card payments, primarily because of holidays or store closures, as many Swiss retail stores are closed on Sundays. In contrast, only 3.8% of ATM-day observations record zero withdrawals.

As shown in Figure 8 in the Appendix, card payments are most common at approximately CHF 3, whereas ATM withdrawals are most common at approximately CHF 100. The figure further reveals that ATM withdrawals are bunched at round values such as CHF 50, 100, and 200—a consequence of fixed banknote denominations—while card payment values follow a distribution with a heavy right tail more closely resembling a log-normal. Furthermore, the figure

shows that on the outage day, low-value withdrawals of CHF 50 and 100 were more common than on normal days, which is consistent with consumers withdrawing smaller amounts to complete immediate purchases.



(a) Distribution of daily ATM withdrawal values by weekday in Switzerland, 2022.

(b) Distribution of daily card payment values at retail stores by weekday in Switzerland, 2022.

Figure 1: Distribution of ATM withdrawals and card payments at retail stores by weekday.

Using the single-transaction card payment and ATM withdrawal data, we construct daily time series of transaction values and volumes for each store and ATM, yielding 32,584 time series spanning three years of daily observations. These store- and ATM-level time series form the basis of our forecasting pipeline, which generates counterfactual predictions of card payments and ATM withdrawals. Figure 1 presents boxplots of the distribution of ATM withdrawal and card payment values by weekday across Swiss ATMs and retail stores. The figures reveal strong day-of-week patterns in both ATM withdrawals and card payments.

5 Methods

To quantify the loss in card payments and the consumer reaction channels, we rely on residuals between granular forecasts and the observed payment volumes and values. In the following sections, we first detail our forecasting pipeline, then specify how we identify the affected stores and define the consumer reaction channels, and finally describe our identification strategy.

5.1 Forecasting pipeline

To generate reliable forecasts of expected card payments and ATM withdrawals, we develop a prediction framework with pretraining and fine-tuning based on seasonal, geographical, and lagged features. The seasonality features include the year, the quarter, the month, the weekday, the day, holidays, and a linear trend. Geographical features capture canton and district information, while lag features incorporate values and volumes from the previous day and the

previous week. Our pipeline produces daily forecasts of both the volume and value of card payments and ATM withdrawals for each individual retail store and ATM in Switzerland, yielding 32,584 models. We employ light gradient boosting machines (LGBMs) as our machine learning method of choice, as this method is computationally efficient while still delivering accurate forecasts. The models are pretrained on a two-year base period (2020–2021) and then used for quarterly rolling predictions for 2022, yielding 365 out-of-sample predictions, with prediction intervals constructed at the 5%–95% level by bootstrapping. The models are first pretrained on the full base-period dataset and then fine-tuned on data specific to each store or ATM for the quarterly rolling forecasts. For card payments, we additionally apply a hurdle approach (Cragg, 1971) to address the frequent occurrence of days with zero transactions (see Table 1): a classification model first predicts whether any card payments occur on a given day, and—conditional on occurrence—a regression model estimates their volume and value. This step is omitted for ATM withdrawals, as zero-withdrawal days are rare (3.8% of ATM-day observations). The full prediction pipeline is illustrated in Figure 2.

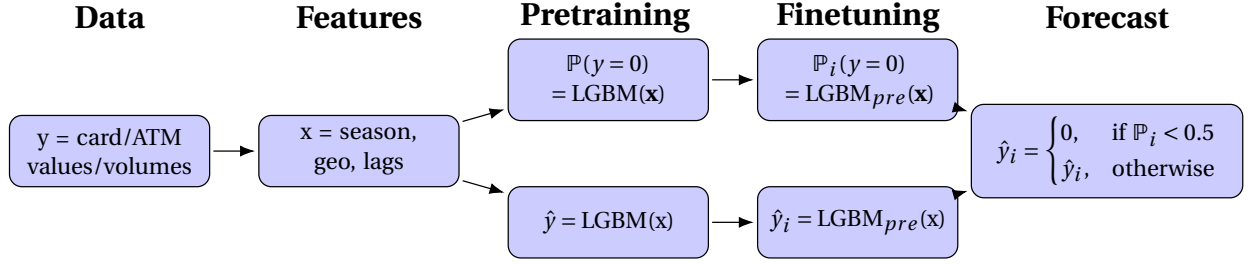


Figure 2: Flow diagram of the forecasting model pipeline.

5.2 Quantification of card sale loss and consumer reaction channels

To quantify the loss in card payments and the corresponding consumer reaction channels, we analyze the residuals between forecast and observed card payments and ATM withdrawals across different store groups. First, to identify outage-affected stores, we classify a store as outage-affected if both its card payment volume and value residuals fall more than 1.5 standard deviations below their expected values on the outage day (see Formula 1). Using this 1.5-standard-deviation threshold as a conservative empirical classification rule, we obtain a set of approximately 2,250 outage-affected stores. The threshold choice is somewhat arbitrary. Our aim is to filter out stores with surprisingly few payments on the outage day while excluding stores exhibiting only ordinary day-to-day fluctuations. To assess whether our results are sensitive to the threshold choice, we conduct a sensitivity analysis in which we vary the classification threshold.

$$S_{\text{out}} = \left\{ s \mid z(\text{res value}_{t_{\text{out}},s}) < -1.5 \wedge z(\text{res volume}_{t_{\text{out}},s}) < -1.5 \right\} \quad \text{where} \quad z(\text{res}) = \frac{\text{res} - \mu(\text{res})}{\sigma(\text{res})} \quad (1)$$

Variables: S = set of stores, s = single store, res = residual / Subscripts: out = with outage, t_{out} = day of outage

We then construct a set of competing stores whose card payment systems were operational on the outage day. For each outage-affected store, we select one store located in the same postal code district with a similar daily card payment volume and value. Similarity is determined using propensity score matching based on seasonality features (see Formula 2). This procedure yields a comparison set that is geographically close and that exhibits similar card payment patterns under normal conditions. The mathematical definition of the set of matched competitor stores is shown below:

$$S_{\text{match}} = \bigcup_{s \in S_{\text{out}}} S_{\text{match}}^{(s)} \quad \text{where} \quad S_{\text{match}}^{(s)} = \left\{ s' \in S_{\text{postal-code}(s)} \mid s \in S_{\text{out}}, s' = \arg \min_{k \in S_{\text{postal-code}(s)}} |\text{Propensity}_k - \text{Propensity}_s| \right\} \quad (2)$$

Variables: S = set of stores, s = single store, Propensity = propensity score / Subscripts: $match$ = matched to outage stores (competitors), s' = most similar store without outage

Finally, to assess whether outage-affected stores experienced a rebound in card payments the following day, we compare their observed payments on the day after the outage with the corresponding forecasts. To quantify excess ATM transactions, we similarly compare forecast and observed ATM withdrawals. The mathematical expressions for the aggregate loss in card payments and the three consumer reaction channels are presented below:

$$\text{Loss card payments}_{t_{\text{out}}, S_{\text{out}}} = \sum_{out \in S_{\text{out}}} \left(\text{Forecast card}_{t_{\text{out}}, out} - \text{Observed card}_{t_{\text{out}}, out} \right) \quad (3)$$

$$\text{ATM residuals}_{t_{\text{out}}} = \sum_{a \in \text{ATM}} \left(\text{Observed ATM}_{t_{\text{out}}, a} - \text{Forecast ATM}_{t_{\text{out}}, a} \right) \quad (4)$$

$$\text{Card residuals competition}_{t_{\text{out}}, S_{\text{match}}} = \sum_{sm \in S_{\text{match}}} \left(\text{Observed card}_{t_{\text{out}}, sm} - \text{Forecast card}_{t_{\text{out}}, sm} \right) \quad (5)$$

$$\text{Card residuals day after}_{t_{\text{out}}+1, S_{\text{out}}} = \sum_{out \in S_{\text{out}}} \left(\text{Observed card}_{t_{\text{out}}+1, out} - \text{Forecast card}_{t_{\text{out}}+1, out} \right) \quad (6)$$

Subscripts: t_{out} = day of outage, S_{out} = set of stores with outage, S_{match} = set of matched stores (competition), $t_{\text{out}} + 1$ = day after outage, out = single stores with outage, a = single ATM, sm = single matched store

5.3 Identification of the causal effect of card losses on consumer reaction channels

Following a forecast-based event-study framework and the double-debiased machine learning literature, we estimate the causal effect of the loss in card payments on the consumer reaction channels. Similarly to Cerqua et al. (2023), we use machine learning forecasts to construct counterfactuals of card payments and ATM withdrawals absent the outage, allowing us to estimate treatment effects without a proper control group. We extend this approach by estimating the continuous effect size of outage intensity—as proxied by card loss—on the consumer reaction channels. Specifically, we use the forecasting pipeline outlined in Section 5.1 to generate counterfactual predictions for card payments and ATM withdrawals based on the same set of

seasonal, geographical, and lagged features. Applying the Frisch-Waugh-Lovell theorem, we obtain residuals—the difference between observed and counterfactual volumes and values—that are net of high-dimensional confounders, as described in Chernozhukov et al. (2018). This allows us to partial out the effect of card payment losses on the proposed consumer reaction channels. We aggregate these residuals to the district level—our most granular common geographical unit across card payment and ATM withdrawal data—and normalize them by the district population to account for varying district sizes. Intuitively, our identification strategy exploits the variation in outage intensity. Districts experiencing a more severe card payment loss per capita should exhibit more pronounced consumer reactions, such as excess ATM withdrawals. We estimate these effects via the following residual-on-residual regressions:

$$\text{ATM residuals}_{t_{out},d}^{pc} = \alpha + \beta_{ATM} \cdot \text{Loss card}_{t_{out},S_{out},d}^{pc} + \gamma_d + \varepsilon_d, \quad (7)$$

$$\text{Card residuals competition}_{t_{out},S_{match},d}^{pc} = \alpha + \beta_{competition} \cdot \text{Loss card}_{t_{out},S_{out},d}^{pc} + \gamma_d + \varepsilon_d, \quad (8)$$

$$\text{Card residuals day after}_{t_{out}+1,S_{out},d}^{pc} = \alpha + \beta_{day\ after} \cdot \text{Loss card}_{t_{out},S_{out},d}^{pc} + \gamma_d + \varepsilon_d, \quad (9)$$

Superscript: pc = per capita

Subscripts: t_{out} = day of outage, d = district, S_{out} = set of stores with outage, S_{match} = set of matched stores (competition), $t_{out} + 1$ = day after outage

We extend the baseline specification by adding district-level controls. The magnitude of consumer reactions to the outage likely varies across districts because of differences in payment infrastructure and cash usage behavior. To account for this heterogeneity, we incorporate a set of district-level controls denoted by γ , derived from our own data. First, to capture payment infrastructure characteristics, we include ATM density—the number of ATMs per 1,000 inhabitants—and merchant density—the number of merchants per 1,000 inhabitants. Second, to capture baseline cash usage, we include the cash share—defined as the volume or value of ATM withdrawals divided by the sum of all ATM and card transactions in the district in 2022. Finally, to control for broader district characteristics, we include the settlement area share and the share of the population aged 65 and above, as provided by the Federal Statistical Office (FSO, 2023).

As a further robustness check, we perform placebo regressions to validate the significance of both our main effect and the potential moderating effects of cash infrastructure—proxied by ATM density—and cash usage—proxied by the cash share—on excess ATM withdrawals during the outage. In our placebo specification, we apply the regression specification with controls to each of the 364 out-of-sample predicted days on which no large outage occurred (Chernozhukov et al., 2024). If the outage day is indeed special, we would expect the coefficient on the outage day to be more statistically significant, larger in magnitude, or of a different sign than the coefficients obtained on normal days.

6 Results

We find that consumers primarily reacted to the card payment system outage by withdrawing excess cash at ATMs. In the following sections, we first show that our forecasting models produce reliable forecasts for card payments and ATM withdrawals with high out-of-sample R^2 values and we show the effect of the outage in the aggregated card payment and ATM withdrawal time series. Second, we identify a set of outage-affected stores and calculate the aggregated residuals for card payment losses and the consumer reaction channels. Third, we causally identify the effect of outage intensity—measured by card payment losses—on consumer reaction channels, with a focus on excess ATM withdrawals.

6.1 Forecasting card payments and ATM withdrawals

Table 2 presents the out-of-sample performance metrics for the card payment and ATM withdrawal forecasting models. The card payment models achieve strong explanatory power, with R^2 values above 80% for both value and volume, while the ATM forecasting models achieve R^2 values above 60% for both value and volume. To benchmark our models, we use the mean absolute scaled error (MASE) (Hyndman & Koehler, 2006), which evaluates forecast performance relative to a naïve baseline that uses the previous day’s volume or value as its predictor. A MASE below 1 indicates that the model outperforms the naïve baseline, while a MASE of 0 represents a perfect forecast. Our forecasting pipeline outperforms this baseline by approximately 65% for card payment values and volumes and by 45% for ATM withdrawal values and volumes.

To evaluate the ability of the card payment models to predict whether any transactions occur on a given day, we use classification metrics, including accuracy, the F1 score, and the AUC. The models perform strongly, correctly predicting days without card payments, with AUC and accuracy values above 98%. This binary classification step is omitted for ATM forecasts, as only 3.8% of days record no ATM withdrawals.

Figures 3a and 3b show the forecast and observed volumes and values of card payments at all Swiss retail stores during the weeks surrounding the outage. All plots include bootstrapped 90% prediction intervals. On the outage day, retail stores in Switzerland were forecast to record approximately 2.48 million card payments totaling CHF 100 million. Notably, the effect of the outage—marked by a red box—is visible even in this aggregated macro-level time series, with

Table 2: Performance metrics of volume and value forecasts of card payments and ATM withdrawals.

	Card		ATM	
	Volume	Value	Volume	Value
R^2	83.1%	80.1%	60.9%	64.5%
$MASE_{lag}$	31.7%	35.1%	52.5%	55.2%
Accuracy	98.1%	98.1%	-	-
F1	92.6%	92.6%	-	-
AUC	98.8%	98.7%	-	-

observed card payments falling below the lower bound of the prediction interval in both value and volume. The opposite pattern emerges in the ATM withdrawal data. Figures 3c and 3d show the forecast and observed ATM withdrawal volumes and values in the weeks surrounding the outage, and on the outage day—again marked by a red box—withdrawals spike sharply, falling well outside the prediction intervals for both volume and value.

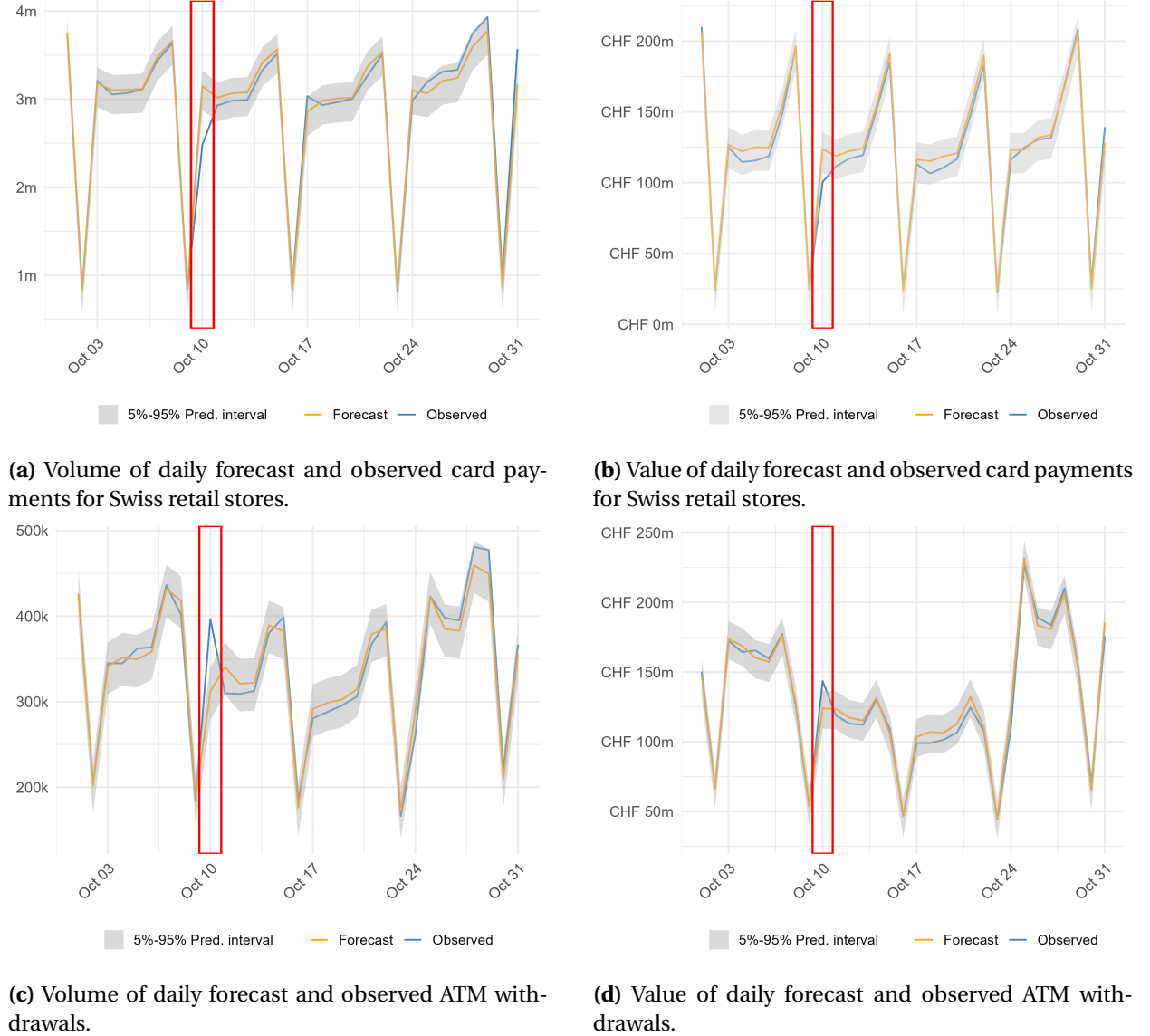


Figure 3: Time series of values and volumes of forecast and observed card payments and ATM withdrawals in the weeks around the card payment system outage (outage marked with a red box).

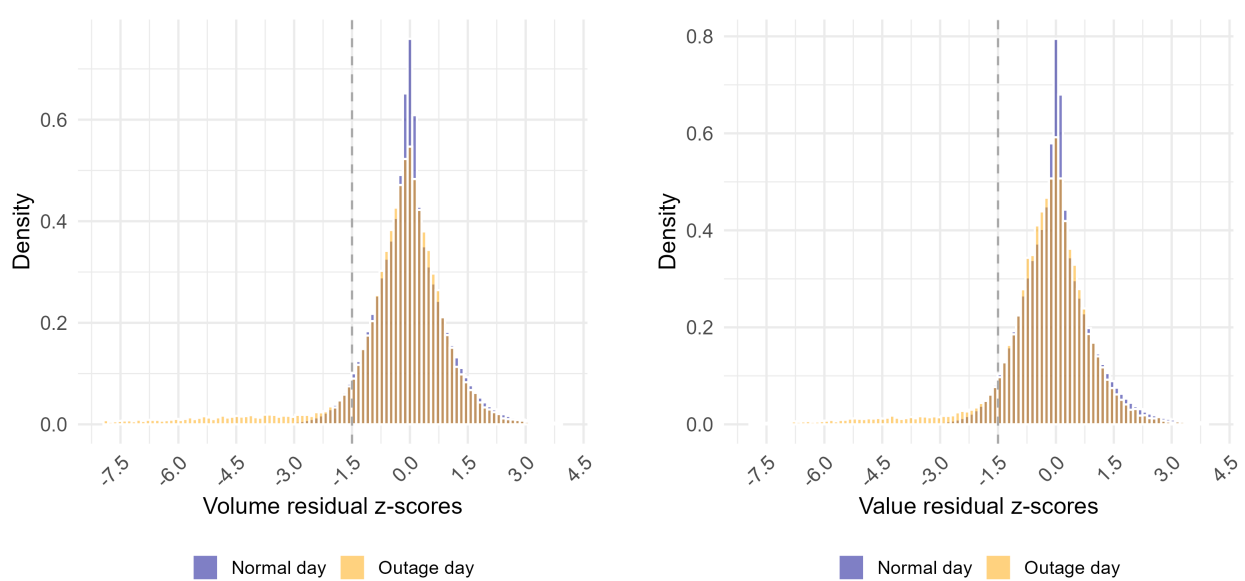
6.2 Card sale loss and consumer reaction channels

To identify the retail stores affected by the outage, we compute z-score normalized residuals between the forecast and observed card payments for each store on the outage day and apply a classification threshold. Figure 4 shows the z-score normalized residuals for both the outage day and normal days in 2022, as well as the outage threshold. While the residual z-scores for normal days follow a near-normal distribution centered on zero, the outage day has a long left tail, indicating that some stores processed significantly fewer card payments than

expected. Stores falling below a threshold of 1.5 standard deviations (as defined in Equation 1) are classified as outage-affected, yielding approximately 2,250 such stores—a conservative approximation of the 2,400 stores of the affected retailer.

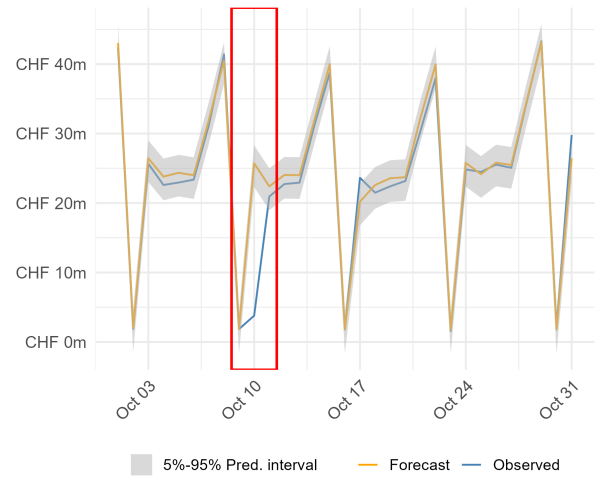
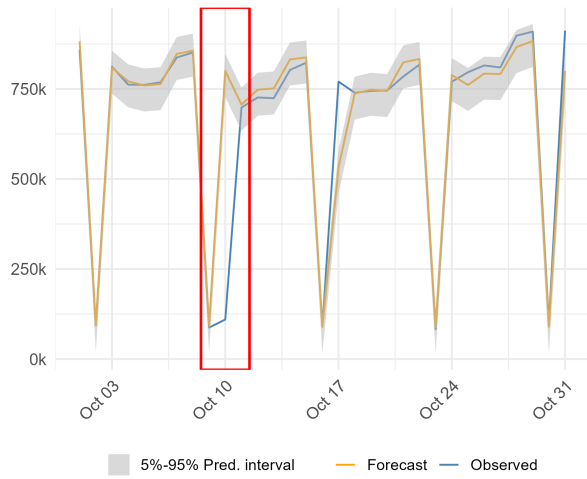
With the set of outage-affected stores defined, we quantify the loss in card payments. Figure 5 shows the daily forecast and observed card payment values and volumes for these stores. Outage-affected stores experienced a loss of approximately 700,000 card payments totaling CHF 22 million. This amount corresponds to roughly 28% of the volume and 22% of the value of forecast card payments across the Swiss retail trade sector on the outage day. The observed card payments at outage-affected stores amounted to approximately 10% of the forecast amount. The fact that the observed card payments at outage-affected stores were not zero can be explained by two factors. First, anecdotal evidence suggests that some stores were still able to process a small number of payments, particularly in the morning. Second, our classification likely includes a small number of stores that were not actually affected by the outage but that nonetheless recorded payment values and volumes more than 1.5 standard deviations below the forecast.

In addition to the loss in card payments, we quantify the excess in ATM withdrawals and other potential consumer reaction channels, namely, whether consumers paid with cards at competing stores with functioning payment systems or returned to outage-affected stores the day after. Figure 6 shows the estimated CHF 22 million loss in card payments alongside the three identified consumer reaction channels. First, compared with forecast ATM withdrawals, there was an excess of approximately CHF 20 million in cash withdrawals, clearly falling outside the prediction intervals. Second, we measure excess card payments at competing stores by matching outage-affected stores with unaffected stores in the same postal code district with similar



(a) Z-score normalized volume residual on outage and normal days. (b) Z-score normalized value residual on outage and normal days.

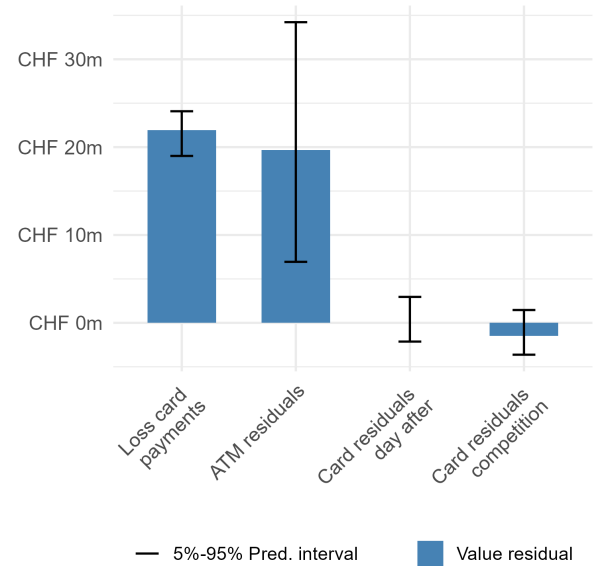
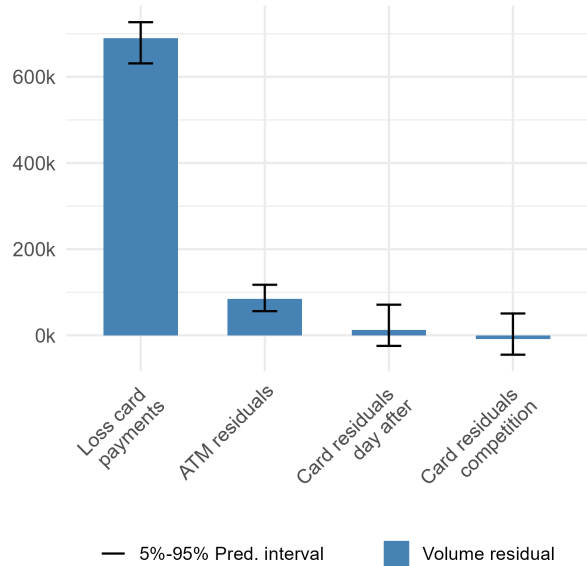
Figure 4: Value and volume z-scores of card payments on the outage day and on normal days.



(a) Volume of daily forecast and observed card payments for outage-affected stores.

(b) Value of daily forecast and observed card payments for outage-affected stores.

Figure 5: Time series of values and volumes of forecast and observed card payments at outage-affected stores in the weeks around the card payment system outage (outage marked with a red box).



(a) Loss in card sales and consumer reaction channels in terms of volume.

(b) Loss in card sales and consumer reaction channels in terms of value.

Figure 6: Absolute card loss and consumer reaction channels on the card payment system outage day.

payment patterns via propensity score matching (see Equation 2), but we observe only a small increase in card payments at these stores. Finally, we consider an excess in card payments at outage-affected stores the day after the outage but find only minimal—and even slightly negative—residuals, suggesting that card payments remained below expectations. The small excess at competing stores and the near-zero residuals the day after are consistent with consumers relying on ATM withdrawals or pre-existing cash holdings, reducing the need to visit competing stores or to delay purchases.

6.3 Effect of card losses on consumer reaction channels

We find that the outage, as measured by card payment losses, had a strong positive effect on ATM withdrawals, while the effects on the other consumer reaction channels were small and mostly insignificant.

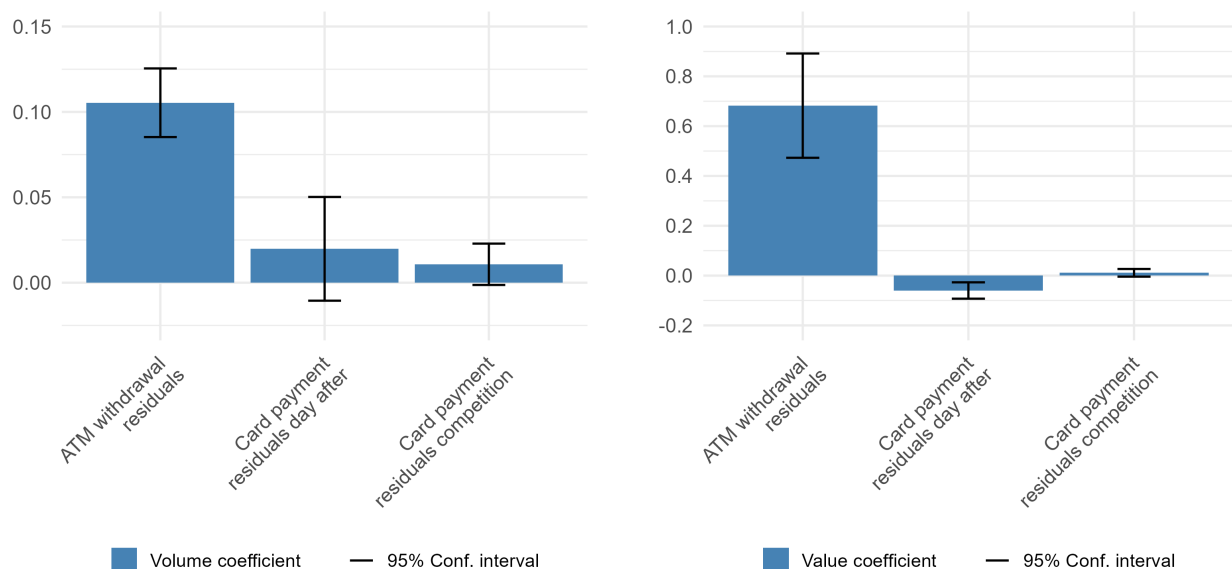
Using a residual-on-residual regression, we estimate the effect of outage intensity—proxied by card payment losses—on ATM withdrawal residuals and the other consumer reaction channels across districts in a base specification and with controls. Visually, there is already a strong correlation between the loss in card payments per capita and excess ATM withdrawals per capita— $R=0.65$ for volume and $R=0.47$ for value—as shown in Figure 9 in the Appendix. Table 3 shows that across all specifications, the volume and value coefficients for card losses on ATM withdrawals are positive, large, and highly statistically significant, indicating that districts experiencing larger card payment losses also exhibit stronger increases in ATM withdrawals. Table 4 in the Appendix shows the regression results with the full set of controls. In terms of volume, the estimated per capita coefficients are 0.11 in the base specification and 0.10 in the specification with controls, indicating that for every 100 lost card payments, there were approximately 11 additional ATM withdrawals. Card payment losses explain approximately 42% of the variance in ATM withdrawal residuals in the baseline specification, increasing to 56% in the specification with additional controls. In terms of value, the estimated per capita coefficients are 0.68 in the base specification and 0.54 in the specification with additional controls, indicating that for every CHF 100 in lost card payments, ATM withdrawals increased by approximately CHF 68 in the base specification. In these specifications, the adjusted R^2 lies between 0.22 and 0.33.

Table 3: Impact of card payment losses on ATM withdrawal residuals: baseline and control specifications.

	Volume ATM		Value ATM	
	Base	Controls	Base	Controls
Card loss	0.105*** (0.010)	0.097*** (0.013)	0.682*** (0.107)	0.535*** (0.134)
Controls	No	Yes	No	Yes
Intercept	Yes	Yes	Yes	Yes
R^2	0.428	0.580	0.224	0.356
Adj. R^2	0.424	0.561	0.219	0.328
Num. obs.	143	143	143	143

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Our results suggest that consumers in districts that were more strongly affected by the outage responded by increasing cash withdrawals at nearby ATMs, which may reflect several mechanisms. First, some consumers may have withdrawn cash and returned to outage-affected stores to complete transactions originally intended to be paid by card. Second, others may have initially relied on cash on hand and subsequently replenished their holdings at ATMs. Third, some



(a) Volume coefficients of card payment losses on consumer reaction channels.

(b) Value coefficients of card payment losses on consumer reaction channels.

Figure 7: Beta coefficients of card payment losses on consumer reaction channel regressions.

individuals may have increased their precautionary cash holdings in anticipation of future outages. However, the data do not allow us to disentangle these mechanisms.

The differences between the volume and value regressions provide further insights into consumer reactions during the outage. The value coefficient is larger in magnitude than the volume coefficient, reflecting the fact that consumers typically withdraw more cash than needed for a single purchase, which is consistent with a precautionary cash holdings motive. Despite their smaller magnitude, the volume coefficients explain a larger share of the variance in ATM withdrawal residuals, as measured by the adjusted R^2 . This finding points to a clearer response along the extensive margin—that is, an increase in the number of people withdrawing cash during the outage. The effect on the intensive margin, namely, the amount withdrawn per capita, is noisier across districts, as is also visible in the correlation plots in Figure 9 in the Appendix.

Using the same residual-on-residual regression setup, we estimate the effect of card payment losses per capita on card payments per capita at outage-affected stores the day after the outage and at competing stores on the outage day. Figure 7 compares these effects across consumer reaction channels based on the baseline regression specification. From a volume perspective, the outage had no significant effect on card payment residuals either at competing stores on the outage day or at affected stores the day after. From a value perspective, card payment residuals at competing stores were similarly insignificant, although we observe a statistically significant decrease of approximately CHF 0.06 in card payments per capita at outage-affected stores the following day. The decrease in card payments the day after the outage is consistent with consumers using up their cash stocks, which they withdrew during the outage. Overall, however, the effects of the outage on the other consumer reaction channels are small and mostly insignificant.

6.4 Heterogeneity and robustness checks of the outage effect on ATM withdrawals

The excess in ATM withdrawals during the outage was more pronounced in districts with denser ATM infrastructure and higher baseline cash usage. We augment the baseline specification with district-level controls to examine whether the outage effect on excess ATM withdrawals was moderated by cash infrastructure—proxied by ATM density—or baseline cash usage—proxied by the cash share. The full results are reported in Table 4 in the Appendix. We find that ATM density has a positive and significant effect on the volume of excess ATM withdrawals, while the cash share has a positive and significant effect on their value. These findings suggest that districts with denser ATM infrastructure experienced a stronger response along the extensive margin—that is, more people withdrew cash during the outage—while baseline cash usage is associated with higher withdrawal amounts. Cash use is higher in rural areas than in cities, whereas ATM density is higher in cities, where the population uses less cash (SNB, 2021, 2025a). This may explain why districts with higher ATM density show a positive effect, as more people were affected by the outage and needed cash.

Our effect—that a loss in card payments leads to excess ATM withdrawals—is robust and stable across different thresholds for the definition of outage-affected stores. To verify this, we re-estimate the baseline regression of card losses on excess ATM withdrawals across a range of alternative classification thresholds (see Appendix Figures 10 and 11). Both the estimated coefficients and the adjusted R^2 values of the model remain stable for thresholds between 0 and -3.5 standard deviations. Interestingly, the effect also persists at a threshold of 0 since all outage-affected stores are contained within this set and the additional stores with residuals close to zero add only little noise. Beyond a threshold of -3.5, the coefficients and R^2 decline sharply, likely reflecting the shrinking sample size—particularly after aggregation to the district level—and the exclusion of some large outage-affected stores.

The positive relationship between card payment losses and excess ATM withdrawals is specific to the outage day. To verify this, we perform placebo regressions on the 364 out-of-sample days on which no major card payment system outage occurred, the results of which are reported in Table 5 in the Appendix. The placebo regressions confirm that the positive relationship between card payment losses and excess ATM withdrawals is specific to the outage day. On normal days, negative card payment residuals are associated with negative ATM withdrawal residuals, suggesting that both variables are driven by common demand factors rather than a substitution effect. For instance, on rainy days, we would expect both fewer card payments and fewer ATM withdrawals. In contrast, the outage-day correlation coefficient and t-statistic are unique in terms of their sign and magnitude, ranking as the largest positive values across all tested days. With respect to the controls, the placebo results indicate that the positive effect of ATM density on the withdrawal volume is also specific to the outage day, with both its correlation coefficient and t-statistic falling in the upper 95th percentile of the placebo distribution. The effect of the cash share on the withdrawal value is less clearly outage-specific, with the outage-day correlation coefficient ranking at only the 60th percentile of placebo days.

7 Discussion

Building on our empirical findings, we discuss their implications for payment system resilience and identify directions for future research.

7.1 Policy implications

This paper shows that cash infrastructure can serve as a resilience buffer during a card payment system outage and that consumers rely on cash as their fallback payment instrument. We demonstrate that a nationwide outage of the card payment system at a large Swiss retail chain resulted in a substantial loss of card payments. However, the presence of accessible cash infrastructure appears to have mitigated some of the negative effects: we estimate that 100 lost card payments led to 11 additional ATM withdrawals and that a loss of CHF 100 in card payments led to CHF 68 in additional ATM withdrawals. This resilience function, however, presumes that cash infrastructure itself is not affected by the outage. Our findings also highlight that consumers rely on cash as their resilience mechanism over other cashless alternatives: we do not find a significant increase in card payments at competing retailers with working card payment systems or at outage-affected stores the day after. While we cannot quantify how much of the lost card payment revenue was recovered in cash at outage-affected stores, our results strongly suggest a collective consumer reaction to obtain cash—whether to complete purchases, replenish cash on hand, or prepare for future outages. However, in 2022, cash still accounted for 36% of all point-of-sale transactions, and the ATM density in Switzerland remained high (SNB, 2023). This raises the question of whether the resilience function of cash infrastructure and consumers' reliance on cash as a fallback payment instrument will persist as cash usage and ATM density continue to decline.

7.2 Future work

Future research should further investigate the extent to which lost card payments can be recovered at outage-affected stores and whether the resilience function of cash infrastructure persists as cash usage and acceptance declines or ATMs become less accessible. First, our study could not measure how much of the loss in card payments was offset by cash payments, as we lack data on cash sales at outage-affected stores. Such data would be valuable for quantifying the actual revenue loss and for determining whether consumers withdrew additional cash in preparation for potential future outages or in anticipation of continued disruption. Therefore, future work should focus on better understanding how consumers use cash and ATM infrastructure during card payment system outages. Second, our study examines only a single outage event. Analyzing multiple outages over time would strengthen external validity and allow researchers to explore whether the resilience function of cash infrastructure persists under declining cash usage and acceptance rates or reduced ATM density. Therefore, future research should prioritize identifying additional outage events and tracking how the resilience function of cash evolves over time.

8 Conclusion

In this paper, we quantify the effects of a nationwide card payment system outage at a large Swiss retailer and show that accessible cash infrastructure can mitigate the negative consequences of such an event. We develop a forecasting pipeline that accurately predicts both card payments and ATM withdrawals, and we use it to identify the stores affected by the outage. We then quantify the loss in card payments and estimate its effect on excess ATM withdrawals and other consumer reaction channels at the district level. Our results show that a one-day outage resulted in a loss of approximately 700,000 card payments worth CHF 22 million, while on the same day, there was an excess of approximately 85,000 ATM withdrawals worth CHF 20 million. Our residual-on-residual regressions suggest that 100 lost card payments were associated with 11 additional ATM withdrawals and that a loss of CHF 100 in card payments was associated with CHF 68 in additional ATM withdrawals. We find only limited evidence of increased card payments at competing stores or on the day after the outage. Our findings suggest that accessible cash infrastructure can serve as a resilience buffer in increasingly cashless societies when card payment systems fail. Furthermore, consumers rely on cash as their primary fallback payment instrument. However, the extent to which this function persists as cash use and infrastructure decline remains an open question.

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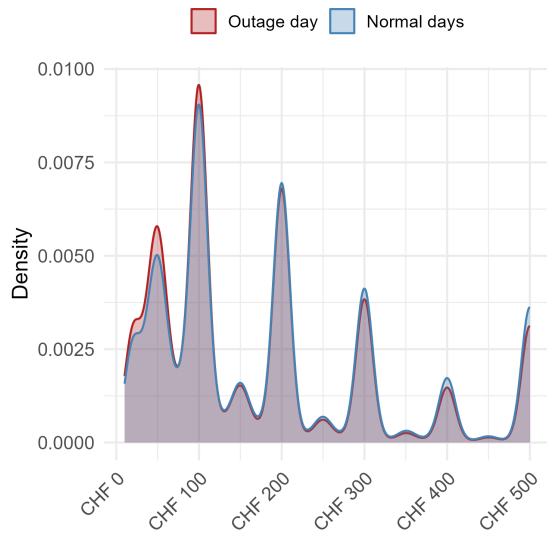
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9 Appendix

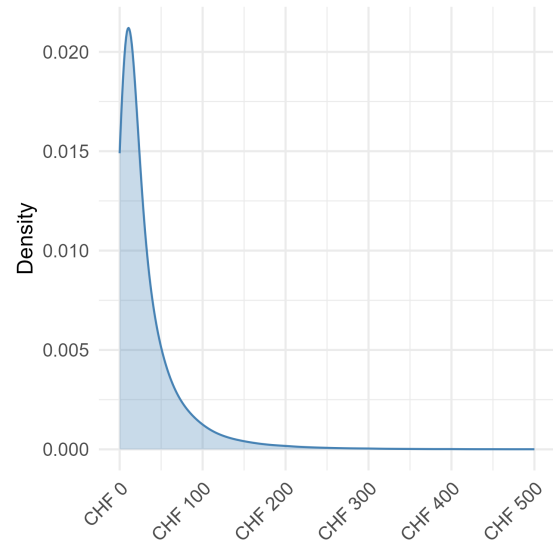
Table 4: Impact of loss in card payments on ATM withdrawal residuals regression with controls.

	Volume	Value
Card loss	0.097*** (0.013)	0.535*** (0.134)
ATM density	0.008*** (0.002)	0.288 (0.794)
Cash share	−0.000 (0.000)	0.055*** (0.020)
Merchant density	−0.000 (0.001)	0.478** (0.198)
Settlement area share	−0.005 (0.003)	−0.141 (1.107)
Population share 65+	0.021 (0.014)	3.617 (5.567)
Controls	Yes	Yes
Intercept	Yes	Yes
R ²	0.580	0.356
Adj. R ²	0.561	0.328
Num. obs.	143	143

Notes: All variables are normalized by district population or are expressed in percentage terms. *Card loss* denotes the per capita loss in the card payment volume and value at outage-affected stores on the outage day. *ATM density* is the number of ATMs per 1,000 inhabitants. *Merchant density* is the number of merchants per 1,000 inhabitants. *Cash share* is the volume or value of ATM withdrawals divided by the sum of all ATM and card transactions per district. *Settlement area share* is the share of the district area classified as a settlement area. *Population share 65+* is the share of the district population aged 65 and above. Standard errors are in parentheses.

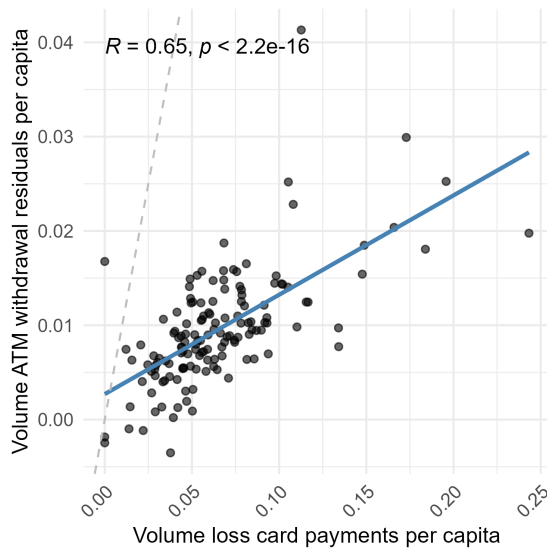


(a) Kernel density estimate of ATM withdrawal values on outage and normal days.

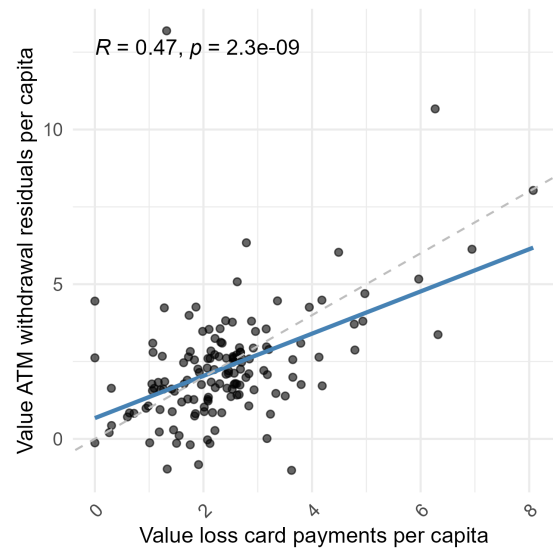


(b) Kernel density estimate of card payment values at retail stores on normal days.

Figure 8: Kernel density estimates (Gaussian kernel, bandwidth = 10) of the distribution of ATM withdrawal and card payment values in Switzerland, 2022.

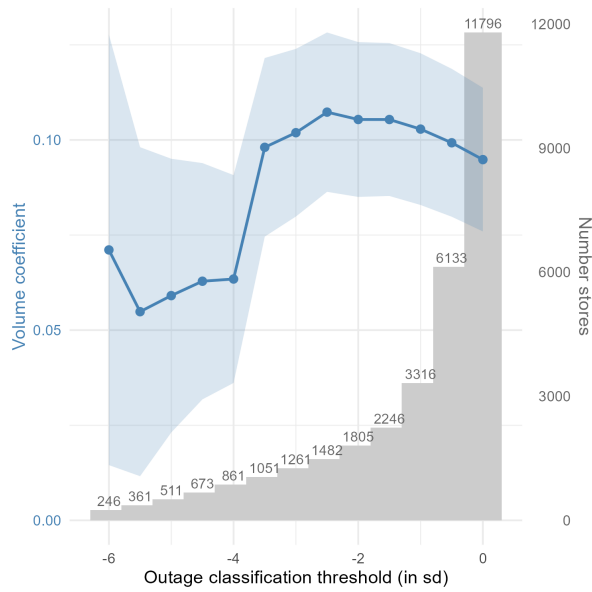


(a) Volume district correlation between the loss in card payments and ATM withdrawal residuals per capita.

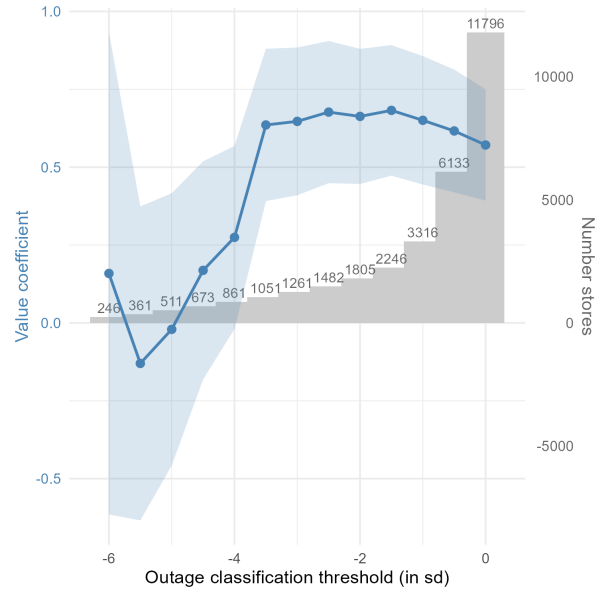


(b) Value district correlation between loss in card payments and ATM withdrawal residuals per capita.

Figure 9: Correlation between volume and value of card payment losses per capita and ATM withdrawal residuals per capita across districts.

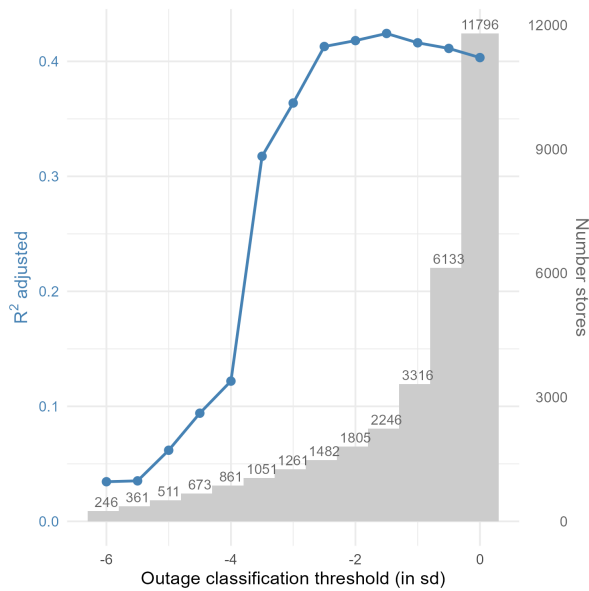


(a) Volume coefficient of card losses on ATM withdrawal residuals regression depending on the outage threshold.

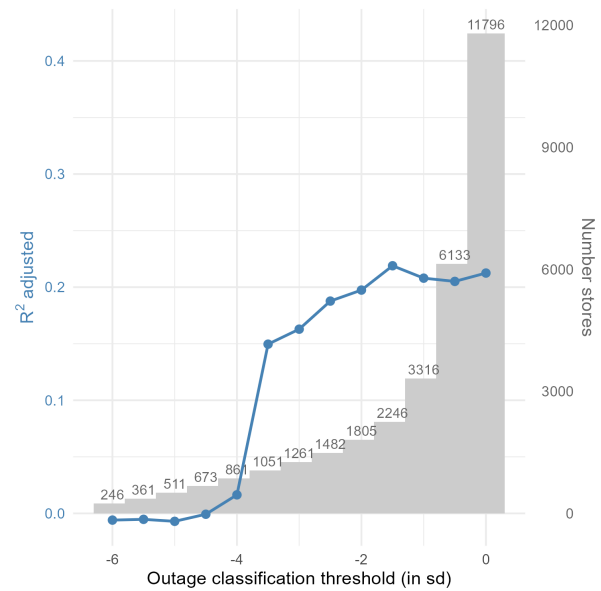


(b) Value coefficient of card losses on ATM withdrawal residuals regression depending on the outage threshold.

Figure 10: Sensitivity analysis of card loss coefficients on ATM withdrawal residuals to the outage store classification threshold (base specification), with store counts and 95% confidence intervals.



(a) Adjusted R^2 of volume card losses on ATM withdrawal residuals regression depending on the outage threshold.



(b) Adjusted R^2 of value card losses on ATM withdrawal residuals regression depending on the outage threshold.

Figure 11: Sensitivity analysis of the adjusted R^2 of card losses on ATM withdrawal residuals regression (base specification) and store count depending on outage store classification thresholds (in standard deviations).

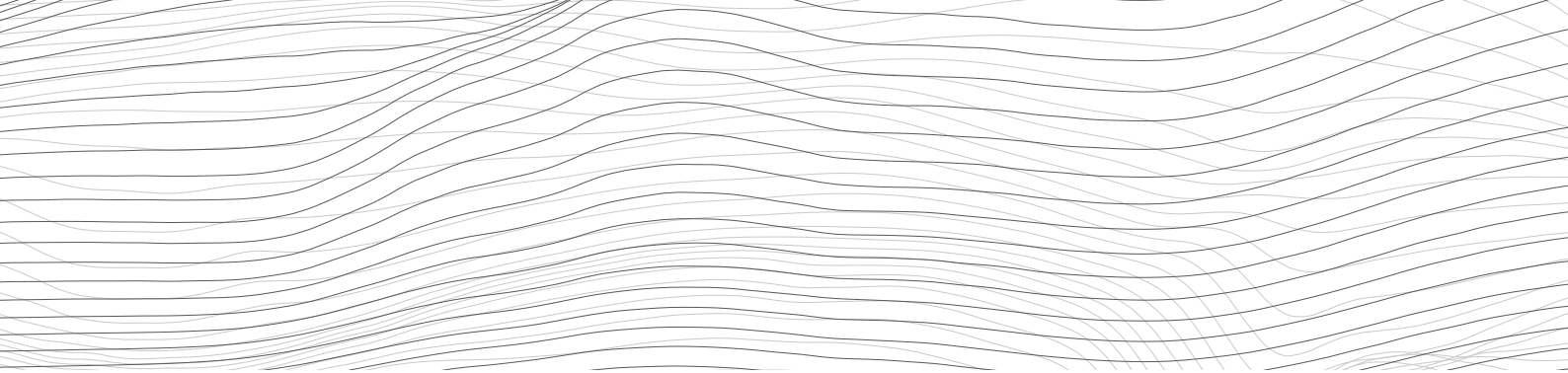
Table 5: Placebo regression analysis comparing coefficient significance and magnitude on outage and normal days.

	Card loss		ATM density		Cash share	
	Volume	Value	Volume	Value	Volume	Value
<i>Outage estimate</i>						
Correlation	0.654	0.474	0.574	0.469	−0.089	0.021
(Percentile)	(100.0%)	(100.0%)	(99.7%)	(97.8%)	(20.7%)	(60.1%)
<i>t</i> -statistic	7.69	3.99	3.70	0.36	−0.14	2.69
(Percentile)	(100.0%)	(100.0%)	(96.7%)	(60.3%)	(43.0%)	(92.8%)
<i>Placebo distribution</i>						
Mean correlation	−0.181	−0.118	−0.064	−0.058	0.011	−0.017
Mean <i>t</i> -statistic	−1.93	−1.22	−0.12	−0.13	0.10	−0.23
Share positive significant	0.028	0.041	0.152	0.129	0.132	0.135
Share negative significant	0.449	0.264	0.154	0.152	0.110	0.201

Notes: The placebo regression analysis allows us to assess whether the significant relationship between card payment losses and excess ATM withdrawals is specific to the outage day or reflects a persistent underlying relationship between the two variables. We further use the placebo distribution to evaluate whether the significant control variables—ATM density and cash share—are similarly specific to the outage day.

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