Cash me if you can: ATM explosions, payment choice, and consumption*

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April 11, 2025

Abstract

We study the consumption effects of a shift from cash to card payments. We exploit 275 explosive attacks on automated teller machines (ATMs) in Germany, which provide plausibly exogenous variation in the availability of cash. Using home scan data, we find that households increase their consumption by 2.3% after an ATM in their vicinity is attacked. Purchases of more expensive, branded products, and temptation goods drive the increase in spending, and the effect largely dissipates after 3 months. Payment diaries from survey data suggest a significant long-term rise in card payments following explosive attacks. Overall, the results are consistent with short-term overspending as consumers transition to digital payments.

Keywords: Household finance, consumption, cash, digital payments, fintech, ATMs

JEL: D12, D14, D91, E21

*The authors are grateful to the State Criminal Police Offices ("Landeskriminalämter") in Germany for providing data on ATM explosive attacks, as well as to Martina Eschelbach, Susann Sieber, and the Research Data and Service Centre at the Deutsche Bundesbank for their support in obtaining data from the payment behavior surveys. We also thank Jochen Wetzel from Nexiga GmbH for sharing ZIP code-level characteristics data. Access to the home scan data is provided by AiMark (http://www.aimark.org), a not-for-profit foundation that supports top academic research with scanner data provided by its data partners YouGov and Kantar. We sincerely thank Alfred Dijs and Elizabeth Ramaker from AiMark for their support with the data. This paper has benefited from funding of the Dutch Research Council (NWO, 406.XS.01.107) and the Erasmus Research Institute of Management (E23.4.006). We thank Sumit Agarwal, David Argente, Martin Brown, Gabriel Chodorow-Reich, Luigi Guiso, Tobin Hanspal (discussant), Sean Higgins, Daniel Karpati, Sarah Lein, Kasper Meisner Nielsen (discussant), Filippo Mezzanotti, Arna Olafsson, Amar Soebhag, and seminar participants at the Lapland Household Finance Summit, the Annual Meeting of the Swiss Society for Financial Market Research, University of Amsterdam, Erasmus University Rotterdam, and Frankfurt School of Finance & Management for helpful comments and suggestions.

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1 Introduction

More and more countries are moving towards cashless societies. The number of purchase transactions with debit or credit cards in the U.S. increased by around 95% from 2010 to 2020, while cash transactions decreased by 55% for the same period (Nilson Report, 2021). Similar trends are observed in the European Union (EU), where cash use has declined in recent years alongside a rise in card payments (see Figure 1). Today, only one out of five day-to-day transactions in the U.S. are paid with cash (Nilson Report, 2021), while cash payments still constitute 59% of point-of-sale transactions in the euro area (European Central Bank, 2022). This shift in payment methods has sparked an important debate among academics and policymakers: what are the effects of a cashless society on households, firms, and the economy? At the macro level, phasing out cash might facilitate "unconventional" monetary policy measures such as negative interest rates. It might also increase tax revenues by constraining the largely cash-based shadow economy. At the household level, cashless payments could reduce transaction costs and potentially enhance household wealth. However, physical cash can also help consumers manage and monitor their spending by providing a tangible limit on their expenses. In fact, the European Central Bank (ECB) notes that one purpose of cash is to "[...] keep track of your expenses. Cash allows you to keep closer control of your spending, for example by preventing you from overspending."[1]

In this paper, we examine the causal impact of payment method choice on household consumption behavior in a developed country where nearly all households have access to a bank account, yet cash remains widely used. We rely on local shocks to the availability of cash, which are unlikely to affect other economic outcomes such as GDP growth or employment. Specifically, we employ a difference-in-differences (DID) research design to study the effects of 275 explosive attacks on automated teller machines (ATMs) in Germany from 2011 to 2019. The setting provides a unique opportunity to study how households adapt their payment behavior and consumption in response to a reduced availability of cash. To analyze these effects, we combine two complementary data sources: home scan data capturing detailed

[1] https://www.ecb.europa.eu/euro/cash_strategy/cash_role/html/index.en.html.

household purchase records and payment diaries from central bank surveys conducted by the Deutsche Bundesbank. We find that households increase their consumption by 2.3% following an attack on a nearby ATM. The rise in consumption is primarily driven by purchases of more expensive, branded products, and temptation goods. The effect is temporary, gradually reverting over three months, and consistent with short-term overspending as consumers adapt to digital payments.

Cash can serve as a tangible budgeting tool, providing consumers with a physical representation of their spending limits. Unlike digital payments, the use of cash often makes spending decisions more concrete, encouraging mindful spending behavior. This awareness can help curb impulsive purchases, while card payments might reduce this awareness and lead to increased consumption.[2] Additionally, consumers may be more attached to cash due to the endowment effect, which suggests that people place a higher value on physical cash than on digital currency (Agarwal, Ghosh, Li, and Ruan, 2024).[3] This attachment can make consumers more reluctant to spend cash, whereas cards lack this psychological barrier. Moreover, accessing cash involves higher transaction costs, such as the time and effort required to visit ATMs, which can serve as a natural restraint on spending. In contrast, card payments eliminate these transaction costs, making transactions more convenient and potentially leading to higher consumption. Together, these factors suggest that switching from cash to card payments may lead to increased spending, at least in the short run, until budget constraints become binding.

Alternatively, card payments may facilitate more responsible consumption, potentially resulting in lower spending compared to cash transactions. Unlike cash, card payments often provide a digital record of each transaction, allowing households to monitor their expenses more effectively. For example, Jonker and Kosse (2013) find that consumers tend to forget small and less recent purchases, which can lead to unintentional overspending. Thus, card payments, particularly in combination with banking apps, can help households track their spending habits, monitor budgets, and maintain a better overview of their financial situation.

[2] See von Kalckreuth, Schmidt, and Stix (2014b) and Jonker (2007) for survey evidence on cash as a budgeting tool and Heath and Soll (1996) and Ameriks, Caplin, and Leahy (2004) for evidence on overspending.

[3] According to the endowment effect, people feel attached to their own (physical) belongings (Anagol, Balasubramaniam, and Ramadorai, 2018). Consequently, in our case, digital payments trigger weaker effects than cash.

Therefore, whether the switch to card payments leads to increased or decreased spending is ex-ante ambiguous and ultimately remains an empirical question.

Identifying the causal effect of payment method choice on spending is challenging due to their complex interdependence. For example, a positive relationship between the choice of cards for payments and spending might be due to reverse causality when consumers prefer cards over cash for larger purchases. Hence, it is the size of the transaction that drives the choice of payment method, rather than the payment method influencing the level of consumption. To overcome this challenge, we exploit explosive attacks on ATMs in Germany as a shock to the availability of cash. By combining these events with payment diaries from the Bundesbank and anonymized transaction-level home scan data from YouGov, we examine the causal effect of payment choice on household consumption. ATM bombings have become a widespread phenomenon in Germany, and using police records of each federal state, we study 275 such incidents between January 2011 and March 2019. In most cases, these attacks destroyed the targeted ATMs, and in some instances, even the entire adjacent bank branch (see Figure 2 for a collage of pictures of exemplary explosive attacks and the usual modus operandi of the perpetrators).[4]

We first investigate the effect of explosive ATM attacks on consumption using YouGov home scan data. To address possible treatment effect heterogeneity and staggered treatment timing, we implement a stacked difference-in-differences (DID) design.[5] Based on a sample of approximately 9,500 households, we find consumers in ZIP codes with an ATM attack increase their consumption by 2.3% relative to consumers in neighboring ZIP codes 90 days after an incident. In absolute terms, consumers spend roughly €16 more over these 90 days. We perform a battery of robustness tests and find that the increase in consumption is robust to alternative treatment definitions, matching procedures, and the inclusion of various sets

[4] Similar to the Nielsen scanner data (e.g., Jaravel, 2018), the YouGov data does not represent the full consumer basket in the German consumer price index (CPI). As illustrated in Appendix Table A1, the YouGov sample includes a wide range of non-durable goods as well as storable goods. Nevertheless, important items such as rent, transportation, and leisure activities that represent large components in the bundle of a representative consumer are missing. Reassuringly, Alvarez-Blaser, Auer, Lein, and Levchenko (2025) demonstrate that CPI calculations for the consumption categories included in the YouGov data closely align with those of the official CPI category price indexes, yielding remarkably similar results.

[5] See de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021), Sun and Abraham (2021), Gormley and Matsa (2011), Deshpande and Li (2019), and Cengiz, Dube, Lindner, and Zipperer (2019).

of fixed effects.

The increase in consumer spending can arise due to at least four possible mechanisms: A decreased ability to track expenses, a reduction of the endowment effect, a decrease in transaction costs, or stress-related coping mechanisms that arise due to higher crime levels. We run a battery of additional tests to shed light on these alternative channels. First, we separate overall consumer spending into the number of products purchased and the price per product. The effect on consumption originates primarily from buying more expensive products, not from buying more goods. Moreover, the consumption increase is accompanied by an increased spending of branded products and temptation goods (i.e., lemonade, sweets and snacks, ice cream, pizza, cake, etc.), even though consumers spend more across almost all product categories (e.g., beverages, food, etc.). By contrast, the consumption of products on sale is lower after treatment. We also find that consumers switch from discounters (such as ALDI or Lidl) to more high-end supermarkets (such as REWE or EDEKA) and local shops. Conditional on consumers shopping in a given store type, however, consumption increases across all shop types, with consumption in supermarkets, local shops, and department stores (+2.5%, +2.7%, +3.1%) increasing by almost twice as much as spending at discounter stores (+1.4%). When we study the temporal dynamics of the main effect, we find the increase in consumption is relatively short-lived and becomes insignificant after 3 months.

Next, we examine whether the treatment effect varies with the availability of alternative ATMs for cash withdrawals. The increase in consumption is more pronounced in areas where the nearest alternative ATM is farther away or where fewer ATMs from the same network are available, in line with ATM explosions leading to changes in ATM usage behavior. Importantly, these findings help to rule out the alternative explanation that heightened stress or fear of violence caused by ATM explosions drives the increased consumption. If emotional responses were the primary driver, we would expect consumption to increase uniformly across treatment areas, regardless of alternative ATM availability. For instance, stress-related coping mechanisms, such as emotional eating, would not depend on the proximity to alternative ATMs. However, the observed stronger treatment effects in areas with fewer or more distant ATMs suggest the consumption increase is more closely linked to the inconvenience of withdrawing cash than to psychological factors, making the alternative explanation unlikely.

We also explore how household and geographic characteristics influence the temporary increase in consumer spending following ATM explosions. At the household level, higher-income households show a more pronounced rise in spending compared to lower-income groups, likely due to fewer financial constraints and greater adoption of card payments. In contrast, although lower-income households may face challenges with budgeting discipline and have lower levels of financial literacy, their tighter budgets may limit their capacity to overspend. Age also relates to the size of treatment effects, with older households exhibiting larger spending increases, presumably because younger consumers are already more familiar with digital payment tools. At the geographic level, more affluent areas also experience stronger consumption effects. These results align with the income heterogeneity in the household-level findings.

We further examine whether consumers indeed switch to card payments when an ATM in their area is affected by an explosive attack. To this end, we rely on payment diaries obtained from the Bundesbank because the home scan data does not contain information on means of payment for the reported transactions. These payment diaries are part of repeated cross-sectional surveys about the consumption behavior of German households. Households in districts with explosive attacks are more likely to use cards as a payment method in the six months after the attack compared to households in non-treated districts by 5.0 percentage points (p.p.). This difference in the usage of cards is persistent and economically sizable, given that households use a card for only 13% of their transactions during our sample period. While we cannot rule out that households withdraw (more) cash from other distant ATMs or bank branches, our evidence based on Bundesbank survey data supports the idea that the increased consumption coincides with a significant switch towards digital payments.

Taken together, the fact that branded and temptation goods drive the increased consumption, as well as the short-lived nature of the effect in combination with the permanent increase in the likelihood of paying by card point towards households' decreased ability to track expenses in the short run. If decreased transaction costs were driving the effect, we would expect the increased likelihood of paying by card to lead to a more permanent increase in consumption. The temporary nature of the increase also contradicts an explanation based on the endowment effect, which is unlikely to diminish over time (Anagol, Balasubramaniam, and Ramadorai, 2018). Consequently, it appears consumers need some time to adapt to digital payments, e.g., by switching to alternative monitoring mechanisms or by running into a binding budget constraint, resulting in a temporary increase in consumption.

Our results are subject to some caveats. First, Germans notoriously rely on cash for daily transactions. However, the payment behavior during our sample period is similar to that of other developed countries in the Euro area (Esselink and Hernández, 2017). Moreover, most Germans are banked and, as such, have the possibility to switch from cash to card payments, a choice that might not be possible in other, less-banked countries. Finally, we exploit a specific type of event, the temporary reduced access to ATMs due to explosive attacks, which allows for a clean identification at the micro level. However, by design, our study cannot speak to aggregate effects due to phasing out cash and therefore complements studies such as Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020).

Related literature: This paper adds to the literature on the effects of digital payments on consumer choices. Our main contribution is to show that consumers temporarily increase their spending after a local shock to the availability of cash.

Experimental evidence by Feinberg (1986) and Prelec and Simester (2001) documents an increase in consumption when people rely on credit cards instead of cash. Using payment diaries of Swiss consumers, Brown, Nacht, Nellen, and Stix (2023), find a positive association between card usage and consumption. Closest to our study, Agarwal, Ghosh, Li, and Ruan (2024) and Choi and Loh (2024) rely on micro data from India and Singapore, respectively. Exploiting negative shocks to the availability of cash, they find mixed evidence for the effect of digital payments on spending. Agarwal, Ghosh, Li, and Ruan (2024) examine the rapid demonetization in India in 2016, which removed most of the existing currency and resulted in a slowdown in economic activity.[6] Comparing individuals with a heavy reliance on cash before the shock to individuals who already adopted digital payments, they find a 1 p.p.

[6] On November 8^{th}, 2016, the government of India unexpectedly declared 86% of the existing currency in circulation illegal tender, effective at midnight. Referred to as "demonetization," this policy resulted in a sharp decrease in the availability of fungible cash because printing press constraints prevented the immediate replacement of the demonetized currency with new notes. The policy's stated objectives were to target black money, reduce corruption, and remove fake currency notes. Chodorow-Reich, Gopinath, Mishra, and Narayanan (2020) show the demonetization was accompanied by a strong reduction in economic activity and lower bank credit growth.

increase in the share of digital payments leads to a 0.81% increase in total consumption. This effect strengthens over time and is attributed to the endowment effect. In contrast, following ATM closures due to operations optimizations or temporary closures (e.g., due to renovations) in Singapore, Choi and Loh (2024) find a rise in saving behavior (i.e., lower spending) when consumers switch to digital payments. Using a local shock to cash availability, we find a temporary increase in consumption, consistent with the budgeting channel. More recently, Mariani, Ornelas, and Ricca (2025) show that depleted cash services resulting from bank heists in Brazilian banks lead to the diffusion of digital payment technologies, with consequences for bank competition and lending. By contrast, we focus on the consumption effects of a shift from cash to card payments.

Another part of this literature examines positive shocks to the availability of bank accounts and digital payment services (as opposed to negative shocks to the availability of cash). Suri and Jack (2016) document an increase in saving and consumption as Kenyan households gain access to the Kenyan mobile money system. Bachas, Gertler, Higgins, and Seira (2021) document that providing Mexican individuals with bank accounts and accompanying debit cards leads to a strong increase in the active usage of accounts, and a 4.9% reduction in consumption relative to income. They argue this effect is due to increased monitoring of cash balances and building trust in the banking sector. Brown, Hentschel, Mettler, and Stix (2022) show that replacing Swiss bank customers' debit cards with contactless debit cards does not affect spending in the aggregate. Gelman and Roussanov (2024) show that consumers receiving an additional payment card temporarily increase their consumption without changing their consumption on their preexisting cards, consistent with models of mental accounting (Thaler, 1985, 1999).

We further contribute to the literature on the role of cash for the aggregate economy. Rogoff (2015) argues that phasing out cash could be useful in allowing interest rates to turn negative and preventing illegal activities. However, a rapid demonetization could result in lower aggregate demand and a loss in economic activity (as shown by Chodorow-Reich, Gopinath, Mishra, and Narayanan, 2020, for the example of India). Alvarez and Argente (2022) document a high welfare loss for consumers forced to pay by card, which is primarily borne by disadvantaged households. Velde (2009) also provides evidence of monetary non-neutrality and show that a sudden drop in cash supply has adverse real economic effects. Alvarez, Argente, Jimenez, and Lippi (2022) further document that the social costs of phasing out cash in an economy in which not all households have access to alternative payment methods outweigh the benefits from reducing illegal activities. Higgins (2024) investigates the distribution of one million debit cards to low-income households in Mexico between 2009 and 2012, revealing that consumers increasingly shifted their spending toward small retailers as these businesses adopted point-of-sale terminals. Finally, Crouzet, Gupta, and Mezzanotti (2023) show that coordination frictions may matter when adopting electronic payment systems. We add to the literature evidence at the micro level paired with plausibly exogenous variation for causal identification in a setting in which aggregate shocks do not intervene.

Finally, we provide evidence that consumers switch to digital payment methods as withdrawing cash becomes more costly. In doing so, we highlight the costs and benefits of the different types of payment methods. Standard theory defines money as a store of value, a medium of exchange, and a unit of account. A few studies extend this view and suggest that money can also serve as a form of memory that helps economic agents track past spending and investments (e.g., Ostroy, 1973; Lucas, 1980; Kocherlakota and Wallace, 1998). In addition, using cash as means of payment may provide explicit budget constraints (e.g., Heath and Soll, 1996; Ameriks, Caplin, and Leahy, 2004; Borzekowski, Kiser, and Ahmed, 2008; von Kalckreuth, Schmidt, and Stix, 2014b) serve as a precautionary buffer in case of costly cash withdrawals (e.g., due to non-operating ATMs as in Alvarez and Lippi, 2009). Relatedly, Attanasio, Guiso, and Jappelli (2002) show that consumers with ATM cards are more sensitive to changes in interest rates. Empirical evidence on the adoption cost of digital payments can be found in Yang and Ching (2014), Schaner (2017), and van der Cruijsen, Hernandez, and Jonker (2017), whereas Arango, Huynh, and Sabetti (2015) examine the role of card acceptance by merchants.

The paper is organized as follows. Section 2 presents the data. Section 3 examines the impact of explosive ATM attacks on consumption. Section 4 explores the mechanisms driving this effect. Section 5 concludes.

2 Data

This paper combines data on explosive attacks on ATMs in Germany with payment diaries and transaction-level consumption data from German households. We compiled a dataset of explosive attacks on ATMs based on police-reported incidents obtained from each of the 16 State Criminal Police Offices ("Landeskriminalämter") in Germany. Since these reports often lack precise location details, we hand-collected ZIP code and municipality information through web searches. We identify 1,246 attacks from 2011 to March 2019, i.e., providing a sufficiently long post-event period before the COVID-19 pandemic. For our empirical analysis, we focus exclusively on the first explosive attack in each ZIP code and ensure that no subsequent attacks in the following 365 days confound the post-period results. Moreover, we only include areas where at least one household has observable consumption data in the treatment and control group, which we introduce below. These criteria yield a final sample of 275 first-time explosive attacks for our main empirical tests.

Figure 3 shows all explosive attacks (blue bars) and those included in our tests (red bars) over time. While the number of attacks was relatively low at the beginning of the sample period, it increased steadily, reaching approximately one attack per day by 2018. Panel (a) in Figure 4 shows the geographic distribution of all ATM bombings at the ZIP code level. Most of the attacks took place in the more densely populated areas in western Germany. The incidents, however, occur throughout the country and are not confined to certain areas or states.

Table 1 provides additional information on the final set of 275 incidents. The events are relatively evenly distributed across ATM networks. Sparkasse, the bank with the most branches in Germany, accounts for 27.6% of incidents, whereas Volksbank and the Cash Group (which includes the four largest German private banks – Deutsche Bank, Commerzbank, Postbank, Hypovereinsbank – and their subsidiaries) each account for roughly 20%. In 7% of cases, an ATM belonging to the CashPool network (primarily including BB-

Bank, National-Bank, Santander Consumer Bank, Sparda-Bank, and Targobank) or another bank was attacked. We could not identify the bank network for 26% of events, as neither the police reports nor related news articles, when available, specified the affected banks or the address.[7]

Moreover, the average zip code has 8.58 ATMs. This number, however, likely overestimates the actual number of easily accessible ATMs for households. During our sample period, most banks in Germany charged fees for customers from other banks to use their ATMs. In 2018, the withdrawal fee at an ATM outside a customer's own bank network ranged from €1.95 to €4.95, with an average (median) of €4.01 (€3.95).[8] This represents a significant cost for German households, whose average cash withdrawal is €189 (Deutsche Bundesbank, 2017).[9] The above-mentioned networks are an exemption, where banks waive ATM usage fees for customers within the same network. When considering only these network-affiliated ATMs, the average number of accessible ATMs per area reduces to 3.47. For the subsample of events for which we also observe the exact address, we find that the average driving distance to the closest alternative ATM is around 5.5 kilometers, which varies between 2.8 to 12.1 kilometers between within-network ATMs. Supporting the relevance of our shock, Choi and Loh (2024) analyze the effects of endogenous ATM closures in Singapore, where ATMs are on average only 100 meters apart. They find a 2.4% increase in digital payment frequency after closures of ATMs. Given that Germany has a much lower population density (240 people per square kilometer versus Singapore's 8,358 per square kilometer) and a much lower ATM density, this estimate likely represents a lower bound for the effect of ATM attacks on digital payment adoption in Germany.

Next, we collect information on whether affected ATMs were eventually restored, as this information will later help us assess the persistence of the effect. To determine ATM restora-

[7]It is important to note that robbers may not always succeed in stealing money from the affected ATMs, which might affect the media coverage of the event. This lack of success could occur due to the rapid arrival of the police at the crime scene, an unsuccessful attempt to trigger the explosion, or the cash cassette remaining intact despite the ATM's destruction.

[8]Source: FMH-Finanzberatung e.K. See: https://www.fmh.de/zinsen-vergleiche/girokonto-dispozinsen/gebuehren-an-geldautomaten.

[9]There are no official statistics on the share of out-of-network withdrawals at banks in Germany. However, according to an article by Stiftung Warentest, Commerzbank reports that only 2% of withdrawals at their ATMs are conducted by customers from outside their ATM network. See: https://www.test.de/Geld-abheben-Fremdgehen-wird-teurer-5094418-0/.

tions, we employ a two-step approach. First, we conduct news searches, though details on when ATMs are restored are rarely available. Therefore, we also search Google Maps by bank name and street location, when available. While this method allows us to confirm the ATM's presence as of September 2024, it does not reveal how quickly it was restored. Therefore, these findings should be interpreted with caution, as some ATMs may have been temporarily restored but later removed due to the ongoing reduction in bank branches across Germany. Our findings indicate that most bombed ATMs for which information is available remained operational as of 2024. In subsequent analyses, we will use this data to investigate whether the treatment effect differs for ATMs that have been restored.

Last, we examine the driving distance of the attacked ATM to the nearest store by store type. On average, attacked ATMs are located 2.7 kilometers from the nearest supermarket and 3.2 kilometers from the nearest discounter, while drug stores and department stores are farther away. These distances indicate that attacked ATMs are generally not in the immediate vicinity of either supermarkets or discounters. More importantly, the similarity in distances between the two store types suggests that any observed consumption effects of ATM attacks are unlikely to be driven by changes in shopping frequency due to store accessibility. For example, if attacked ATMs were disproportionately closer to supermarkets, households might not only adjust their withdrawal behavior but also reduce their trips to these stores, leading to a decline in supermarket spending and an increase in other store types. However, the data suggest that this mechanism is unlikely at play, reinforcing the idea that any changes in consumption are more plausibly linked to shifts in cash availability rather than altered shopping routines.

To examine the impact of these explosive attacks on consumption, we merge them with comprehensive home scan consumer data from YouGov, which acquired the consumer panel business of the Gesellschaft für Konsumforschung (GfK) in 2023. The data have been provided by AiMark (Advanced International Marketing Knowledge). Available from 2009, the data comprise around 30,000 households, representing a stratified sample of German households. In the YouGov panel, households document their consumption by scanning the barcode of each product bought, and by entering volume and price paid for the products. The identification of products via the Global Trade Item Number allows for a standardized classification of purchased items. Households also provide information about the stores, including the names of the retail chains. The consumption data includes fast-moving and storable consumer goods, which include food and beverages, as well as household and personal care items, but largely lacks any form of durable purchases. The database has been employed in prior studies (e.g., Beck and Lein, 2020; Beck et al., 2020; Bachmann et al., 2023) and is comparable to the Kilts-Nielsen Consumer Panel for the U.S., which has been widely used in economics research (e.g., Bronnenberg et al., 2015; Coibion et al., 2022; D'Acunto et al., 2021). Overall, after the merge with ATM data, our main sample consists of 9,567 households that performed 1,447,082 shopping trips.

Although the home scanner data offers extensive coverage of households' consumption over time, it lacks information regarding the means of payment. To study the effect of ATM explosive attacks on household payment behavior, we rely on data from surveys and payment diaries of German households commissioned by the Deutsche Bundesbank. Between 2008 and 2020, the Bundesbank conducted a cross-sectional household survey on "Payment behaviour in Germany" at three-year intervals, with each wave consisting of a different sets of households. The aim of the survey is to assess households' attitudes towards various payment methods and to understand how households manage payments for goods, services, and other daily expenditures. For our analysis, we use the survey responses of the 2011, 2014 and 2017 waves.[10]

The survey consists of two parts: 1) a computer-assisted personal interview including questions about standard demographics and 2) the respondents' payment habits and a payments diary participants complete in the three to seven days following the interview. Participants

[10] As in our main analysis on household consumption, we exclude the 2020 wave to avoid confounding effects driven by the COVID-19 pandemic on households and their consumption, shopping and payment choices. Those payment diaries also document the amount of spending. However, self-reported spending data often suffer from rounding issues, resulting in "heaped" data with large numbers of responses at particular expenditure levels, which may not be random and can introduce both measurement error and bias in the estimated effects (e.g., Heitjan and Rubin, 1991; Pudney, 2008; Browning, Crossley, and Winter, 2014; Ruud, Schunk, and Winter, 2014). For instance, consumers may round their expenditures differently depending on the payment method–e.g., rounding up when paying with cash due to psychological tendencies or pricing structures, such as prices ending in €5.95. To avoid such bias, we rely on the more detailed and comprehensive household scanner data to analyze consumption. Additionally, the YouGov panel allows for longitudinal tracking of household consumption, offering the advantage of observing the spending behavior of households over time.

are asked to record all their spending during these days, except for regularly recurring payments, such as rent or insurance premiums. In addition to recording the individual amount of expenditure, they are required to specify the means and place of payment. In total, 2,098, 2,019, and 2,061 households provide answers to the questionnaire and a completed payment diary for the waves in 2011, 2014, and 2017, respectively.

It is important to note that the payment choice analysis is at the district level (as opposed to the ZIP code level) because it is the smallest geographic unit available in both survey waves that also allows a direct match with the ATM explosion data. The Bundesbank surveys different individuals in each wave, i.e., we cannot compare transactions by the same individuals across the three survey waves. Moreover, the overlap of districts that appear in both waves and experience an ATM attack between them is extremely limited, with only a handful of such cases. Given this data structure, in the analysis, we compare treated and non-treated districts within the same survey wave while controlling for household as well as time-varying district-level covariates that may influence payment behavior. According to the official "Payment behavior in Germany" reports by the Bundesbank, the sample of respondents is representative of people over the age of 18 residing in private households in Germany.[11]

3 Explosive ATM attacks and consumption

We begin by constructing a sample of treated and control households for each explosive attack on an ATM. Treated shopping trips are conducted by households located within a ZIP code where an ATM attack occurred, whereas the control group consists of households located at least 10 kilometers but no more than 50 kilometers away from the treated area. This gap ensures that we do not include control households close enough to be affected by spillover effects from the treated area, which is particularly important in rural regions with low ATM density. For each event, we create separate subsamples of treated and control households, and then stack these subsamples across events to run a stacked DID regression (see, e.g.,

[11] For more detailed information on the Bundesbank survey and details on the sampling procedure, see von Kalckreuth, Schmidt, and Stix (2014a).

Gormley and Matsa, 2011; Deshpande and Li, 2019; Cengiz, Dube, Lindner, and Zipperer, 2019). Control areas are never treated and must be within the same state as the treated area to ensure that public and school holidays, as well as store opening hours, are comparable between the treatment and control groups. Panel (b) in Figure 4 shows that the distribution of treatment and control areas largely follows the entire universe of bombings in Germany in Panel (a).

3.1 Main result

To estimate the impact of ATM explosions on consumption, we run the following DID regression on the home scan panel data:

$$\ln \text{Consumption}_{e,h(z),d,s} = \beta \text{Post}_{e,z,d} \times \text{Treated}_{e,z} + \eta_{e,h(z)} + \phi_{e,d} + \psi_{h(z),s} + \epsilon_{e,h(z),d,s}, \qquad (1)$$

where Consumption is total spending (in euros) per shopping trip, defined as the sum over all purchased items by household h on day d in store s. e denotes the respective explosive attack (event) and z is the ZIP code.

In the regression, the interaction term $\text{Post}_{e,z,d} \times \text{Treated}_{e,z}$ captures the causal impact of ATM explosions on household consumption. $\text{Post}_{e,z,d}$ is set to 1 for all shopping trips in the subsample after an ATM attack and 0 otherwise, and we use pre-periods of up to 90 days prior to the event and up to 360 calendar days after the event as post period. We trim consumption data at the 1st and 99th percentiles to remove outliers. Standard errors are clustered at the event level. We include event-household fixed effects to control for time-invariant household characteristics and event-calendar day fixed effects to account for broader time-varying factors, such as economic conditions or seasonal trends, within each event-specific subsample. Additionally, we include household-store fixed effects to control for household preferences related to store choice.

Note that our analysis is conducted at the shopping trip level. This granular approach allows us to control for a wide array of fixed effects (e.g., shop fixed effects) and ensures a consistent research design throughout the paper. Additionally, consumers in the YouGov database change their reporting behavior from month to month. By examining consumption at the shopping trip level, we assume that the observed trips are representative of consumers' unobserved shopping behavior. However, this intensive-margin approach makes it challenging to infer aggregated monthly or weekly consumption. For instance, treated consumers may make fewer but larger shopping trips. To address this concern, Table A4 in the Appendix shows that the number of trips per month remains unaffected by our events, suggesting that any increase in consumption per trip results in higher overall monthly consumption.

Table 2 compares average characteristics of treated and control shopping trips in the month before an explosive attack on an ATM. Overall, the consumption behavior and household characteristics of treated and control households are remarkably similar. The average spending per shopping trip by a treated household amounts to €23.51 compared to €23.79 for the control group. The number of purchased items and the average item price are also comparable across the two groups. When looking at monthly consumption behavior, both groups report an average monthly consumption per capita of around €92, which results from ten shopping trips spread across four days. Furthermore, our sample primarily consists of two-person households with an average household income between €1,500-2,999 and an average age of 40-60. As ATMs are more likely to be located in more densely populated areas, it is unsurprising that treated households live in more urban areas. As German ZIP codes are designed such that the population per ZIP code is roughly similar throughout Germany, a higher ATM density in treated areas might bias against finding an effect of ATM bombings on consumption because households might be able to switch to other ATMs more easily.

Table 3 shows the main result. For a post period of 30 days, consumption per shopping trip increases by 2.3% in treated relative to control areas (column (1)), which is statistically significant at the 1% level. The effect exhibits similar magnitudes after 60 and 90 days. In absolute terms, a 2.3% increase in consumption corresponds to €16.32 over 90 days.[12] This estimate likely represents a lower bound of the effect, as our sample pertains primarily to fast-moving consumer goods reported by the panelists. Finally, for post periods exceeding 180 days, the treatment effect decreases in magnitude. The results suggest the effect reverts

[12] 2.3% × 23.42 (avg. consumption per trip) × 10.10 (number of trips in 30 days) × 3.

after 90 days, which we will further explore in Section 4.2.

To interpret these effects causally, we require that treated and control households behaved similarly before the ATM attacks and would have continued to behave similarly absent the event. The latter is inherently untestable but we can provide graphical evidence to evaluate whether this parallel trends assumption is plausible. In Figure 5, we plot the coefficients from regressing the natural logarithm of total consumption on interactions of the treatment indicator with relative time dummies. The omitted category are shopping trips in the $[-60d, -30d]$ window before an incident, denoted by $t = -1$. The shaded area indicates 90% confidence intervals. The pre-treatment coefficients are close to 0, suggesting no apparent violation of the parallel trends assumption. In line with Table 3, the consumption of treated households relative to control households is elevated during the first four months after an explosive ATM attack, and the effect reverts subsequently. Hence, our identifying assumption that treated and control households would have continued to behave similarly in the absence of an incident appears plausible.

3.2 Treatment intensity

We next examine whether the treatment effect varies based on the availability of alternative ATMs where consumers could withdraw cash. We expect the increase in consumption to be stronger in treated ZIP codes where no other ATMs are operated by the same ATM network or where the nearest alternative ATM is farther away, as consumers would need to travel farther to withdraw cash from another ATM.

Table 4 presents the results. Columns 1-3 split the sample based on whether ATMs from the same network as the attacked ATM are present within the ZIP code. For comparison, Column 1 replicates the baseline analysis from Column 3 in Table 3 but limits the sample to the 200 events with available information on the treated ATM network. We find that the treatment effect is slightly smaller for this subset of events with available network information. More importantly, the sample split in Columns 2 and 3 suggests that the increase in consumption is higher for the subset of events with no alternative ATMs in the treated ZIP code area. Specifically, consumption rises by 2.8% in these cases–twice the effect observed in the other subsample.

Columns 4-6 examine the driving distance from the treated ATM to the nearest alternative ATM from the same network. Using a median split of the sample based on the driving distances between the ATMs, we find that the treatment effect is somewhat stronger when the nearest alternative ATM is farther away.[13]

The evidence presented in Table 4 indicates a stronger treatment effect when the nearest available ATM is farther away, supporting the idea that ATM explosions lead to changes in ATM usage behavior. This finding also helps rule out an alternative explanation that ATM explosions negatively affect personal well-being by increasing stress levels and fear of violence. Under this alternative, the observed increase in consumption could be interpreted as a coping mechanism to restore well-being. For instance, fear and stress might trigger emotional eating, leading individuals to seek comfort in food to temporarily alleviate negative emotions (e.g., Adam and Epel, 2007; Torres and Nowson, 2007). However, this explanation is inconsistent with the stronger treatment effects observed when the nearest alternative ATM from the same network is farther away. Instead, the results point to changes in ATM withdrawals as the primary driver of the effect.

3.3 Robustness

We examine the robustness of the main result in Table 5. We focus on a post period of 90 days similar to Column 3 in Table 3. In Column 1, we remove the household $\times$ shop fixed effects, whereas Column 2 replaces them with shop fixed effects. We continue to find a positive and significant effect of ATM explosions on consumption, although the DID coefficients slightly decrease in magnitude, suggesting that some of the effect comes from shopping trips by the same household within the same shop. In Column 3, we add several control variables (income, age, and household size) and the estimated coefficient barely changes.

Column 4 removes "local shops" similar to mom-and-pop shops. In the YouGov database, these shops do not belong to a larger chain. Typically, these stores will be smaller, family-

[13] Due to the different data requirements, we obtain samples of different sizes and we cannot directly compare the baseline effects across the two sets of regressions. A comparison within each set of regressions across attacks with different characteristics and relative to the relevant baseline is meaningful, though.

held shops such as bakeries or butcheries. These smaller stores often do not provide the possibility of cashless payments (e.g., to save fees related to card payments) or require a minimum purchase amount (e.g., €10) to be able to pay by card. Thus, consumers who might want to pay by card after an ATM incident might be unable to do so (or even avoid such stores) or need to increase their consumption. On the other hand, these stores often sell more expensive products with higher quality. Therefore, we might also observe increased consumption in these stores driven by consumers seeking branded or high-quality products when they switch to card payments. Consequently, we examine the robustness of the main result when excluding these stores from our sample. In Column 4, we find a slightly smaller coefficient compared to the full sample, in line with the idea that consumers might consume more in local shops after switching to card payments. Importantly, however, the main result is robust to excluding local shops.

Column 5 focuses exclusively on bombings for which the attacked ATM was eventually restored and operational as of September 2024 (see Section 2 for variable construction). By limiting the sample to events with restored ATMs, we can address concerns that the observed treatment effect is merely driven by temporary switches to card payments due to the short-term unavailability of ATMs. In the table, we find a positive and statistically significant effect of 1.7%, which is slightly smaller but similar to the baseline effect of 2.3% from Table 3, suggesting that the result also holds in the subsample of events in which the ATM was eventually restored (and giving consumers the possibility to switch back to cash payments). However, this result should be interpreted with caution, as the decision to replace an ATM is endogenous, and we are only able to observe operational ATMs several years after the explosive attack occurred.

Column 6 excludes shops that offer point-of-sale cash withdrawals ("cash at till"). Many German supermarket chains introduced this service during the 2010s, with some early adopters as far back as 2003. For instance, REWE, a large upscale supermarket chain in Germany, allowed free cash withdrawals in 2003 for transactions of at least €20. Such withdrawals could potentially bias our results in several ways. First, customers might switch to potentially more expensive supermarkets to be able to withdraw money at the till. Second, the minimum transaction requirement, which ranges from €5 to €20, might induce consumers to spend more to be able to withdraw cash. Third, stores might introduce cash at till in response to increasing difficulties in accessing cash due to ATM explosions. However, the results indicate that excluding transactions from stores where cash at till is available does not affect our findings.

Table A2 in the Appendix investigates alternative sample definitions. Columns 1 to 3 add events during the COVID-19 pandemic to the sample (up until March 2022), resulting in another 101 events. The treatment effect remains robust but decreases in magnitude, likely because more and more consumers had already switched to card payments before and in the early stages of the pandemic, resulting in a weaker treatment in the first stage. Finally, in Columns 4 to 6, we extend the treatment definition to ZIP code areas within 5 kilometers of the ZIP code with an attacked ATM. As the YouGov panel does not directly survey households in every treated ZIP, this definition adds another 38 events. Consistent with the ATM explosions representing a locally confined shock to close-by households, going farther away from the treated ZIP code results in a smaller but statistically significant estimated coefficient.[14]

Table 2 documents that treated shopping trips are from more urban areas than control trips. Our research design exploiting local shocks to the availability of cash makes it unlikely that other economic outcomes are affected contemporaneously. Nevertheless, local economic or geographic differences could still drive our effect. Therefore, we perform a coarsened exact matching (CEM) algorithm, which improves the comparability of treated and control trips based on observable characteristics. Specifically, we bin the zip code population and area into 20 quantiles based on 5% increments and exact-match the treatment and control groups on those bins. We weight the observations with the inverse of the bin size so that treatment and control observations resemble each other along the matching variables. We omit treated and control observations that remain unmatched. Table A5 in the Appendix shows that the geographic differences between treatment and control ZIP code areas disappear, which arises mostly from the selection of more urban control areas. Column 1 of Appendix Table A6

[14] Table A3 in the Appendix shows that the main result is also robust to alternative levels of clustering of standard errors.

confirms that the main result is robust to this alternative matching procedure with both economic and statistical significance being similar to the results in Table 3.

4 Mechanism

At least three mechanisms are potentially consistent with our results so far. The first potential mechanism is overspending due to a decreased ability to track and monitor expenses or a perceived increase in available funds. Second, consumers may increase their spending as the endowment effects inherent to physical currency vanish. The third channel is a rational increase in consumption due to a decrease in transaction costs. In this section, we aim to disentangle these possible alternative channels.

The first mechanism relates to how households manage their cash. Survey responses indicate that many consumers view cash not only as a means of payment but also as a budgeting tool to track their spending (von Kalckreuth, Schmidt, and Stix, 2014b). When households switch from cash to card payments, they lose this physical budgeting constraint, potentially leading to increased spending. Additionally, instead of switching to card payments after ATM attacks, some consumers may travel to more distant ATMs or bank branches to withdraw cash. To minimize the frequency of trips and reduce travel costs, they might withdraw larger amounts of cash. Consequently, carrying more cash increases their perceived budget at hand and may further encourage additional spending.

The second mechanism involves the reduction in transaction costs associated with using card payments. The convenience of card payments eliminates the need for frequent cash withdrawals, reducing the associated transaction costs, which might be physical travel time or mental costs. This ease of access to funds may promote more frequent purchases, contributing to an overall increase in spending, which could potentially enhance consumer welfare. To explore which of these mechanisms are more likely to explain our main results, we run a number of additional empirical tests.

4.1 Source of increased consumption

To better understand the underlying reasons of increased consumption, we first examine the effect by breaking total consumption into its components. Table 6 decomposes consumption per trip into the number of purchased items and the average price per item. We observe that most of the relative increase in consumption in treated households comes from the decision to purchase more expensive products, although consumers also purchase slightly more products as well: 90 days after treatment, the average price per product has increased by 1.6% (significant at the 1% level), whereas consumers buy roughly 0.7% more products (insignificant at conventional levels).[15]

Moreover, the granularity of the YouGov data allows for an even further decomposition of the increase in consumption. In Table 7, we study the increase in consumption for different types of product categories in our sample. As not every shopping trip includes products from all product categories, we set the euro amount to 0 when the respective category is not included in a given trip. Thus, in contrast to Table 3 consumption can also be 0. Consequently, we perform Poisson regressions as Cohn, Liu, and Wardlaw (2022) suggest. Columns 1 and 2 in Table 7 examine the change in consumption across temptation goods and all other products separately. We define temptation goods as lemonade, sweets and snacks, desserts, cake, pizza, and related snacks stored in the freezer. We observe that the increase in consumption for temptation goods is considerably stronger than for all other goods (2.8 vs. 1.8%).[16]

Columns 3 and 4 distinguish branded from private label products, which are white-label products carrying no brand or the brand of the store selling the product. These products are typically cheaper than branded products. We observe that most of the increase in consumption comes from more expensive branded products.

Finally, Columns 5 and 6 compare products on sale to non-sales products, where we define a product as being on sale whenever the price is at least 10% below the regular price.

[15] When we apply the CEM algorithm and re-run the analysis, in Columns 2 and 3 of Appendix Table A6, we find even stronger differences: the price effect amounts to 1.7% and the quantity increases by only 0.3% .

[16] While economically meaningful, the difference of the interaction coefficients is not statistically significant at conventional levels.

Following Eichenbaum, Jaimovich, and Rebelo (2011) and Kehoe and Midrigan (2015), we first calculate "regular prices" defined as the most frequently observed (modal) price per barcode and supermarket chain within a ±2-month window around the focal month. To ensure robustness, we require at least three months of observed price data within this window. A purchase is classified as a sales transaction if the price is at least 10% below the regular price; otherwise, it is considered a non-sales transaction. Following local ATM attacks, consumers have no increased propensity to buy products currently on sale, whereas the consumption of products sold at or above their regular price goes up, consistent with the earlier result that consumers purchase more expensive products. Those results imply that treated consumers are less price-sensitive or price-aware.[17]

We next look at the different types of stores consumers go to. Following the definitions in the YouGov database, we distinguish between discounters, drug stores, supermarkets, department stores, and local stores (i.e., typically smaller stores such as bakeries). Table 8 provides the results. Panel A investigates the likelihood of a shop visit. Here, the dependent variables are dummy variables set to 1 if a trip relates to the shop type in the column title and 0 otherwise. Panel B examines the natural logarithm of total consumption for trips conditional on a trip to the respective shop type listed in the column titles.

Consistent with consumers opting for more expensive products, Panel A finds that consumers replace cheaper discount stores with more expensive supermarkets as they switch to digital payments. Interestingly, consumers' tendency to shop in local stores remains unchanged, potentially because the limited availability of cashless payments in German local stores offsets the propensity to buy more expensive products. Panel B confirms that irrespective of shop type, consumers increase their spending. However, we find the weakest increase in cheaper discount stores.[18]

[17]In the appendix, we show in Table A7 that, with the exception of body and healthcare products, a consistent increase in consumption across all other five top-level product categories as defined by the YouGov exists (beverages, confectionary, food, fresh food, and near food). In other words, the increase in consumption represents a more general pattern and is not limited to a single product category.

[18]Interestingly, the increase in consumption also holds in the subsample of large chain supermarkets, where throughout the sample, consumers could already pay by card before an ATM attack, as payment terminals were already widely available in this store type. Thus, the endogenous rollout of payment terminals following an ATM attack is unlikely to drive our results. Moreover, since the installation of payment terminals takes time—particularly before the COVID-19 pandemic—it is unlikely that shops' rapid adoption of card payments drives the consumption effect documented in Figure 5.

The analysis of the different components of households' consumption suggests that the increase in spending is driven not only by purchasing more expensive, branded products but also by a stronger inclination toward temptation goods. These patterns are consistent with the idea that reduced cash management—whether through the use of card payment methods or by households carrying more cash after larger, less frequent withdrawals—leads to reduced monitoring ability of available funds, ultimately resulting in higher overall consumption and seems less consistent with the idea of a more efficient management of funds and reduced transactions costs.

4.2 Temporal evolution of the effect

We next examine the effect of explosive ATM attacks on consumption over time. If the increase in consumption after households switch from cash to card payments were due to lower transaction costs associated with digital payments, we would expect a permanent shift in consumption after an ATM explosion. Similarly, if the endowment effect were driving the increase in consumption, we would expect a more prolonged effect, as it is unlikely to diminish over time (Anagol, Balasubramaniam, and Ramadorai, 2018; Agarwal, Ghosh, Li, and Ruan, 2024). By contrast, if households merely need some time to adapt to the new means of payment, we would expect a more transitory effect. For example, when using card payments, consumers might need to find new ways of effectively tracking their financial expenses.

Table 9 examines the treatment effect over time. We now extend the post-period to 540 days after an ATM explosion. Column 1 shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip on interactions of the treatment indicator with relative time dummies. The omitted category is shopping trips in the $[-90d, -1d]$ window before an ATM attack. Consistent with Figure 5, we find that most of the effect comes from the 90 days after the treatment, with later shopping trips exhibiting small and insignificant increases in their magnitude.

In the previous subsection, we see the increase in consumption is mainly driven by households purchasing more expensive goods rather than increasing the number of purchased goods. In Columns 2 and 3, we further decompose the aggregate effect beyond the first 90 days after the explosive attacks on ATMs. Specifically, the reversal in the aggregate consumption effect could originate from a decline in the initial increase in the price of items purchased, as households potentially revert back to buying less expensive products. Alternatively, the price effect could remain elevated, with a decrease in the quantity of items purchased accounting for the decline in total consumption. Our evidence suggests the price component primarily drives the reversal: households initially increase their spending on more expensive items, but this effect fades after 90 days, as shown in Column 3. Meanwhile, the quantity component in Column 2 remains stable throughout the post-period, with no significant changes in the number of products purchased over time.

Taken together, these findings suggest that the temporary increase in consumption primarily reflects a short-lived shift toward purchasing higher-priced items, which subsides after households adjust to using card payments. This pattern aligns with an initial adjustment period, after which households re-establish their original spending composition, suggesting that the effect is transitory rather than driven by permanent changes in transaction costs or the endowment effect.

4.3 Cross-sectional heterogeneity

To further explore the mechanism behind the temporary increase in consumer spending, we examine how household and geographic characteristics influence the impact of ATM explosions on average consumption. At the household level, the YouGov scanner data is limited to information on income and age.

The relationship between income and the effect of switching from cash to card payments on consumption is ambiguous and may operate through two opposing mechanisms. On the one hand, lower-income households are more likely to rely on cash as a budgeting tool due to tighter financial constraints and the need to manage expenses carefully (Thaler, 1985; Heath and Soll, 1996). Restricting access to cash may weaken this budgeting discipline in the short run, as households lose the tangible constraint cash payments provide. Furthermore, lower-income households often exhibit lower levels of financial literacy[19], which may amplify

[19]See Almenberg and Dreber (2015), Bottazzi and Lusardi (2021), Cole, Paulson, and Shastry (2014), Grinblatt,

the risk of overspending when transitioning to card payments. Financially less sophisticated households may find it harder to adapt their budgeting strategies to card payments and are more susceptible to the reduced "pain of payment" (Prelec and Loewenstein, 1998). These two aspects could lead to higher levels of overspending among lower-income households.

On the other hand, the effect may be weaker for lower-income households for two reasons. First, these households have less disposable income to increase consumption significantly, even after switching to card payments. Notably, card payments in our sample period are almost exclusively made using debit cards, which do not allow consumers to spend beyond their current account balances.[20] Thus, the switch from cash to card represents a change in the means of payment rather than access to additional funds, potentially limiting any increase in spending for households with limited financial resources.[21] Second, they may be less inclined to adopt digital payments, even when access to cash is restricted, due to aversion to new payment technologies or a perceived lack of trust in digital systems (Jonker, 2007; Schuh and Stavins, 2010; Arango, Huynh, and Sabetti, 2015; Stavins, 2018). Therefore, overspending might be less pronounced among lower-income households. These different mechanisms and arguments suggest contrasting effects of income on spending, making it ultimately an empirical question.

Models 1 and 2 in Table 10 follow Table 3 but split the sample into two groups using a median net household income (approximately €2,500) observed in the month before treatment. Our analysis indicates that 90 days after treatment, households in both income categories show an increase in spending. Importantly, however, the consumption increase is most pronounced among the high-income households, presumably the least financially constrained group: households with above-median income show a 2.9% rise in consumption, whereas the bottom half exhibits an increase of only 1.7%. These findings align with the idea that lower-income households may be less able to increase consumption due to tighter budget

Keloharju, and Linnainmaa (2011), Guiso and Jappelli (2005), and Lusardi and Mitchell (2014).

[20] According to the Bundesbank payment diaries, credit cards accounted for only 1.8% of transactions in 2011, 1.3% in 2014, and 1.6% in 2017. The corresponding shares for debit cards were 13.4%, 15.3% and 18.9%, whereas cash remained the dominant payment method, used in 82.0%, 79.1% and 74.3% of transactions, respectively (Deutsche Bundesbank, 2014, 2017).

[21] Most consumers in Germany have access to an overdraft facility but this facility does not change when moving from cash withdrawals to debit card payments, and as such an ATM explosion that triggers card usage does not temporarily increase the available resources.

constraints, even after switching to card payments. Additionally, the weaker effect among lower-income households could reflect their lower likelihood of adopting card payments, as they may prefer to continue using cash despite restricted ATM access. However, it is challenging to disentangle these explanations, as our main dataset does not include information on the means of payment, making it difficult to directly assess the extent of card adoption across income groups.

The relationship between age and the effect of switching from cash to card payments on consumption is equally complex. Younger consumers, being more familiar with digital technologies, are possibly more likely to adopt card payments when access to cash is restricted. However, this familiarity may also mean they have already integrated card payments into their financial habits and developed alternative tools, such as budgeting apps, to track expenses effectively. As a result, their spending behavior may not be significantly disrupted by the transition. Alternatively, younger individuals may lack financial literacy due to limited exposure to formal financial education and practical experiences with managing money (Agarwal, Driscoll, Gabaix, and Laibson, 2009; Korniotis and Kumar, 2011; D'Acunto, Hoang, Paloviita, and Weber, 2023). Cognitive development and priorities during adolescence and early adulthood often focus on immediate needs and social experiences, leaving less attention to long-term financial planning. In contrast, more mature consumers often rely more heavily on cash, meaning the shift to card payments introduces a significant disruption to their financial routines. However, their greater resistance to adopting digital payments or reliance on established spending habits may limit the extent of overspending.

Our empirical analysis in Models 3 and 4 of Table 10, representing a median split by age, shows that the largest effect on consumption occurs among older households (aged 55 and above). This finding aligns with the idea that older households are less likely to have used card payments before treatment (e.g., von Kalckreuth et al., 2014a) and face higher adoption costs for digital budgeting tools such as mobile apps. By contrast, the smaller effect observed for younger households likely represents a lower-bound estimate, given their greater familiarity with digital payments prior to treatment. However, as noted earlier, it remains challenging to disentangle the overall consumption effect within each household group into components driven by card payment adoption versus changes in spending behavior, as our primary dataset does not directly capture payment methods.

To complement the household-level heterogeneity, we investigate geographic heterogeneity at the ZIP code level using variables related to local economic characteristics, kindly provided by Nexiga GmbH.[22] Table 11 shows the results of our analysis for two ZIP code characteristics: average purchasing power and the financial products purchasing power, which is the share of purchasing power spent on financial products, in each ZIP code. The results indicate that the consumption effect of ATM explosions is stronger in areas with higher purchasing power and a greater presence of financial products, suggesting more affluent areas exhibit a larger increase in consumption. These results align with the findings from our household-level analysis, where higher-income households showed a more pronounced increase in spending. The consistency across both household- and ZIP code-level analyses suggests that the positive effect on spending in wealthier areas may be driven by two complementary factors: wealthier households are (1) more likely to adopt card payments when cash becomes less accessible and (2) less financially constrained, allowing for greater room to overspend.

Importantly, the purchasing power of financial products could also serve as a proxy for higher financial literacy in the area. Our evidence suggests that, for wealthier households, the effects of reduced financial constraints and a tendency toward overspending may outweigh any potential mitigating influence of financial literacy on spending discipline. Hence, while financial literacy might attenuate overspending, the results indicate that the ease of card payments and the reduced "pain of payment" effect likely drive a net increase in consumption.

4.4 Explosive ATM attacks and payment choice

Finally, we study whether households indeed switch to card payments after explosive attacks on ATMs. This analysis sheds further light on the question of whether a switch to digital payment contributes to the previously documented short-term increase in consumption. For this exercise, we use cross-sectional survey data from the 2011, 2014 and 2017 waves of the Bundesbank payment diaries, which capture household payment behavior at three distinct

[22] For more information, see https://nexiga.com/daten/.

points in time. Unlike a panel dataset, which would allow us to follow the same households over time and analyze within-household variation, our data consist of different households in each wave. As a result, within-household comparisons over time are not possible, and the overlap of districts that appear in at least two waves and experience an ATM attack between them is extremely limited, with only a handful of such cases. Given this data structure, we do not include event-district fixed effects, as they would absorb most of the variation. Instead, we include event-wave fixed effects, which allow us to compare treated and non-treated districts within the same survey wave while controlling for household as well as time-varying district-level covariates that may influence payment behavior.

It is important to note that this analysis is at the district level (as opposed to the ZIP code level) because it is the smallest geographic unit available in both survey waves that allows a direct match with the ATM explosion data. In our setting, a district is defined as treated if at least one of its ZIP codes has experienced an explosive attack on an ATM and if the district consists of ten or fewer ZIP code areas. This restriction ensures that households in treated districts are more likely to be directly affected by the attack, as larger districts with many ZIP codes reduce the likelihood of household-level treatment. For the control group, we do not impose the same restriction on district size, as there is no equivalent treatment effect that requires interpretation at the ZIP code level. Instead, we only exclude districts with more than 50 ZIP code areas to maintain comparability. In the Appendix, Table A8 provides univariate comparisons for the treatment and control groups. While we do observe a few differences in geographic characteristics, such as area and population size, most of the characteristics between the two groups are similar, with normalized differences below 0.25.

We run the following linear probability model based on the matched sample of ATM attacks and Bundesbank payment diaries:

$$\begin{aligned}\text{Card transaction}_{e,h(d),j,w} = {} & \beta \text{Post}_{e,d,w} \times \text{Treated}_{e,d} + \gamma \text{Treated}_{e,d} + \delta \text{Post}_{e,d,w} \\ & + \phi_{e,w} + \epsilon_{e,h(d),j,w},\end{aligned} \tag{2}$$

where Card transaction$_{e,h(d),j,w}$ is a dummy set to 1 for each transaction j by household h in survey wave w that is paid by card, and 0 otherwise. Treated is a dummy set to 1 for transactions conducted by households located within district d with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Control areas also need to be located within the same state in Germany and must never be treated. Post is set to 1 for all transactions in both treated and control districts where an ATM attack occurred within the year preceding the survey. As in our previous analysis of household spending, we use a stacked DID approach and add event-wave fixed effects to our regression framework.

Table 12 presents the estimation results for Equation (2) across different specifications and for two post-treatment periods: six and twelve months after an ATM attack. We find that households in affected districts are more likely to use a card for payments in the six months following the attack compared to those in non-treated districts. In our most saturated specification (Model 3), which includes controls for household and district characteristics as well as fixed effects for spending location, weekday, and transaction size quintiles, card usage increases by 5 p.p. Given a pre-treatment cash usage rate of around 13%, this represents a sizable shift. The effect remains significant over the one-year post-treatment period, suggesting that individuals do not revert to their original payment behavior even after the ATM has been replaced.

It is important to reiterate that this analysis is conducted at the district level. Assuming no spillover effects into unaffected ZIP codes within treated districts, the observed 5 p.p. increase in card usage at the district level suggests that the effect in directly treated ZIP code areas could be even larger. Given that there are, on average, 5.50 times more ATMs per district than per ZIP code,[23] the estimated effect for directly treated ZIP code areas could approach 27.50 p.p.

The results suggest that households switch to card payments after ATM attacks, providing evidence that the observed increase in consumption is linked to this shift in payment behavior. This finding complements the consumption analysis by indicating that disruptions to cash availability push households toward greater reliance on digital payments. However, some caution is warranted when interpreting the magnitude of the effect, as our empirical setting

[23]The average number of ATMs per district is 47.15, while the average number per ZIP code is 8.58, implying a district-to-ZIP ratio of approximately 5.50.

relies on cross-sectional differences across districts rather than within-household variation, and the analysis is limited to a sample of ATM attacks in smaller districts to ensure a sufficient treatment effect. Nevertheless, our findings are consistent with recent work by Mariani, Ornelas, and Ricca (2025), who document that unexpected bank heists involving explosives disrupt cash supply services and trigger a lasting shift toward digital payments.

5 Conclusion

In this paper, we examine the effect of digital payments on consumption, using explosive attacks on ATMs in Germany as an exogenous shock to cash availability. In ZIP code areas affected by these shocks, consumption increases by 2.3%, accompanied by an increase in card payments. Although the shift to card payments is permanent, the increase in consumption largely subsides after three months, indicating that the effect is not sustainable in the long run. We further find that the increase in consumption is predominantly driven by wealthier and older households purchasing more expensive products and temptation goods.

Taken together, these results suggest that temporary overspending may occur as consumers transition to digital payments. As more countries move toward cashless societies, helping consumers manage card payments effectively could be beneficial. One potential solution is user-friendly banking apps—particularly for older generations—that integrate budgeting tools, effectively serving as a form of robo-advising for consumption and savings (D'Acunto and Rossi, 2023).

References

Adam, Tanja C., and Elissa S. Epel, 2007, Stress, eating and the reward system, *Physiology & Behavior* 91, 449–458.

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson, 2009, The age of reason: Financial decisions over the life-cycle with implications for regulation, *Brookings Papers on Economic Activity* 2009, 51–117.

Agarwal, Sumit, Pulak Ghosh, Jing Li, and Tianyue Ruan, 2024, Digital payments and consumption: Evidence from the 2016 demonetization in India, *The Review of Financial Studies* 37, 2550–2585.

Almenberg, J., and A. Dreber, 2015, Gender, stock market participation and financial literacy, *Economics Letters* 137, 140–142.

Alvarez, Fernando, and David Argente, 2022, Consumer surplus of alternative payment methods, Working paper, University of Chicago.

Alvarez, Fernando, David Argente, Rafael Jimenez, and Francesco Lippi, 2022, Cash: A blessing or a curse?, *Journal of Monetary Economics* 125, 85–128.

Alvarez, Fernando, and Francesco Lippi, 2009, Financial innovation and the transactions demand for cash, *Econometrica* 77, 363–402.

Alvarez-Blaser, Santiago, Raphael Auer, Sarah M. Lein, and Andrei A. Levchenko, 2025, The granular origins of inflation, Working paper, Harvard Business School (Alvarez-Blaser), Bank for International Settlements (Auer), University of Basel (Lein), and University of Michigan (Levchenko).

Ameriks, John, Andrew Caplin, and John Leahy, 2004, The absent-minded consumer, Working paper, The Vanguard Group.

Anagol, Santosh, Vimal Balasubramaniam, and Tarun Ramadorai, 2018, Endowment effects in the field: Evidence from India's IPO lotteries, *The Review of Economic Studies* 85, 1971–2004.

Arango, Carlos, Kim P. Huynh, and Leonard Sabetti, 2015, Consumer payment choice: Merchant card acceptance versus pricing incentives, *Journal of Banking & Finance* 55, 130–141.

Attanasio, Orazio P., Luigi Guiso, and Tullio Jappelli, 2002, The demand for money, financial innovation, and the welfare cost of inflation: An analysis with household data, *Journal of Political Economy* 110, 317–351.

Bachas, Pierre, Paul Gertler, Sean Higgins, and Enrique Seira, 2021, How debit cards enable the poor to save more, *The Journal of Finance* 76, 1913–1957.

Bachmann, Rüdiger, Benjamin Born, Olga Goldfayn-Frank, Georgi Kocharkov, Ralph Luetticke, and Michael Weber, 2023, A temporary VAT cut as unconventional fiscal policy, Working paper, University of Notre Dame.

Beck, Guenter W., Hans-Helmut Kotz, and Natalia Zabelina, 2020, Price gaps at the border: Evidence from multi-country household scanner data, *Journal of International Economics* 127, 103368.

Beck, Günter W., and Sarah M. Lein, 2020, Price elasticities and demand-side real rigidities in micro data and in macro models, *Journal of Monetary Economics* 115, 200–212.

Borzekowski, Ron, Elizabeth K. Kiser, and Shaista Ahmed, 2008, Consumers' use of debit cards: Patterns, preferences, and price response, *Journal of Money, Credit and Banking* 40, 149–172.

Bottazzi, L., and A. Lusardi, 2021, Stereotypes in financial literacy: Evidence from PISA, *Journal of Corporate Finance* 71, 101831.

Bronnenberg, Bart J, Jean-Pierre Dubé, Matthew Gentzkow, and Jesse M Shapiro, 2015, Do pharmacists buy Bayer? Informed shoppers and the brand premium, *The Quarterly Journal of Economics* 130, 1669–1726.

Brown, Martin, Nicole Hentschel, Hannes Mettler, and Helmut Stix, 2022, The convenience of electronic payments and consumer cash demand, *Journal of Monetary Economics* 130, 86–102.

Brown, Martin, Yves Nacht, Thomas Nellen, and Helmut Stix, 2023, Cashless payments and consumer spending, Working paper, Study Center Gerzensee and University of St. Gallen (Brown), Swiss National Bank (Nacht and Nellen), and Oesterreichische Nationalbank (Stix).

Browning, Martin, Thomas F. Crossley, and Joachim Winter, 2014, The measurement of household consumption expenditures, *Annual Review of Economics* 6, 475–501.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, 2019, The effect of minimum wages on low-wage jobs, *The Quarterly Journal of Economics* 134, 1405–1454.

Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayanan, 2020, Cash and the Economy: Evidence from India's Demonetization, *The Quarterly Journal of Economics* 135, 57–103.

Choi, Hyun-Soo, and Roger K. Loh, 2024, Physical frictions and digital banking adoption, *Management Science* 70, 6483–7343.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2022, Monetary policy communications and their effects on household inflation expectations, *Journal of Political Economy* 130, 1537–1584.

Cole, S., A. Paulson, and G.K. Shastry, 2014, Smart money? The effect of education on financial outcomes, *The Review of Financial Studies* 27, 2022–2051.

Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti, 2023, Shocks and technology adoption: Evidence from electronic payment systems, *Journal of Political Economy* 131, 3003–3065.

de Chaisemartin, Clément, and Xavier D'Haultfœuille, 2020, Two-way fixed effects estimators with heterogeneous treatment effects, *American Economic Review* 110, 2964–2996.

Deshpande, Manasi, and Yue Li, 2019, Who is screened out? Application costs and the targeting of disability programs, *American Economic Journal: Economic Policy* 11, 213–248.

Deutsche Bundesbank, 2014, Zahlungsverhalten in Deutschland 2014, Frankfurt am Main.

Deutsche Bundesbank, 2017, Zahlungsverhalten in Deutschland 2017, Frankfurt am Main.

D'Acunto, Francesco, Daniel Hoang, Maritta Paloviita, and Michael Weber, 2023, IQ, expectations, and choice, *The Review of Economic Studies* 90, 2292–2325.

D'Acunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber, 2021, Exposure to grocery prices and inflation expectations, *Journal of Political Economy* 129, 1615–1639.

D'Acunto, Francesco, and Alberto G. Rossi, 2023, New frontiers of robo-advising: Consumption, saving, debt management, and taxes, in Agostino Capponi and Charles-Albert Lehalle, (eds.) *Machine Learning and Data Sciences for Financial Markets*, 9–28 (Cambridge University Press).

Eichenbaum, Martin, Nir Jaimovich, and Sergio Rebelo, 2011, Reference prices, costs, and nominal rigidities, *American Economic Review* 101, 234–262.

Esselink, Henk, and Lola Hernández, 2017, The use of cash by households in the Euro area, Working paper, European Central Bank (ECB).

European Central Bank, 2022, Study on the payment attitudes of consumers in the Euro area (SPACE), Frankfurt am Main.

Feinberg, Richard A., 1986, Credit cards as spending facilitating stimuli: A conditioning interpretation, *Journal of Consumer Research* 13, 348–356.

Gelman, Michael, and Nikolai Roussanov, 2024, Managing mental accounts: Payment cards and consumption expenditures, *Review of Financial Studies* 37, 2586–2624.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, *Journal of Econometrics* 225, 254–277.

Gormley, Todd A., and David A. Matsa, 2011, Growing out of trouble? Corporate responses to liability risk, *The Review of Financial Studies* 24, 2781–2821.

Grinblatt, M., M. Keloharju, and J. Linnainmaa, 2011, IQ and stock market participation, *The Journal of Finance* 66, 2121–2164.

Guiso, L., and T. Jappelli, 2005, Awareness and stock market participation, *Review of Finance* 9, 537–567.

Heath, Chip, and Jack B. Soll, 1996, Mental budgeting and consumer decisions, *Journal of Consumer Research* 23, 40–52.

Heitjan, Daniel F., and Donald B. Rubin, 1991, Ignorability and coarse data, *The Annals of Statistics* 19, 2244–2253.

Higgins, Sean, 2024, Financial technology adoption: Network externalities of cashless payments in Mexico, *American Economic Review* 114, 3469–3512.

Imbens, Guido W., and Jeffrey M Wooldridge, 2009, Recent developments in the econometrics of program evaluation, *Journal of Economic Literature* 47, 5–86.

Jaravel, Xavier, 2018, The unequal gains from product innovations: Evidence from the U.S. retail sector, *The Quarterly Journal of Economics* 134, 715–783.

Jonker, Nicole, 2007, Payment instruments as perceived by consumers: Results from a household survey, *De Economist* 155, 271–303.

Jonker, Nicole, and Anneke Kosse, 2013, Estimating cash usage: The impact of survey design on research outcomes, *De Economist* 161, 19–44.

Kehoe, Patrick, and Virgiliu Midrigan, 2015, Prices are sticky after all, *Journal of Monetary Economics* 75, 35–53.

Kocherlakota, Narayana, and Neil Wallace, 1998, Incomplete record-keeping and optimal payment arrangements, *Journal of Economic Theory* 81, 272–289.

Korniotis, George M, and Alok Kumar, 2011, Do older investors make better investment decisions?, *The Review of Economics and Statistics* 93, 244–265.

Lucas, Robert E., 1980, Equilibrium in a pure currency economy, *Economic Inquiry* 18, 203–220.

Lusardi, A., and O.S. Mitchell, 2014, The economic importance of financial literacy: Theory and evidence, *Journal of Economic Literature* 52, 5–44.

Mariani, Lucas A., José Renato H. Ornelas, and Bernardo Ricca, 2025, Banks' physical footprint, digital payment technologies, and fintech growth, Working paper, Bocconi University (Mariani), Central Bank of Brazil (Ornelas), and Insper (Ricca).

Nilson Report, 2021, U.S. consumer payment systems, Issue 1210, December.

Ostroy, Joseph M., 1973, The informational efficiency of monetary exchange, *American Economic Review* 63, 597–610.

Prelec, Drazen, and George Loewenstein, 1998, The red and the black: Mental accounting of savings and debt, *Marketing Science* 17, 4–28.

Prelec, Drazen, and Duncan Simester, 2001, Always leave home without it: A further investigation of the credit-card effect on willingness to pay, *Marketing Letters* 12, 5–12.

Pudney, Stephen, 2008, Heaping and leaping: Survey response behaviour and the dynamics of self-reported consumption expenditure, Working paper, University of Essex.

Rogoff, Kenneth, 2015, Costs and benefits to phasing out paper currency, *NBER Macroeconomics Annual 2014* 29, 445–456.

Ruud, Paul A., Daniel Schunk, and Joachim K. Winter, 2014, Uncertainty causes rounding: An experimental study, *Experimental Economics* 17, 391–413.

Schaner, Simone, 2017, The cost of convenience? Transaction costs, bargaining power, and savings account use in Kenya, *Journal of Human Resources* 52, 919–945.

Schuh, Scott, and Joanna Stavins, 2010, Why are (some) consumers (finally) writing fewer checks? The role of payment characteristics, *Journal of Banking & Finance* 34, 1745–1758.

Stavins, Joanna, 2018, Consumer preferences for payment methods: Role of discounts and surcharges, *Journal of Banking & Finance* 94, 35–53.

Sun, Liyang, and Sarah Abraham, 2021, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects, *Journal of Econometrics* 225, 175–199.

Suri, Tavneet, and William Jack, 2016, The long-run poverty and gender impacts of mobile money, *Science* 354, 1288–1292.

Thaler, Richard, 1985, Mental accounting and consumer choice, *Marketing Science* 4, 199–214.

Thaler, Richard H., 1999, Mental accounting matters, *Journal of Behavioral Decision Making* 12, 183–206.

Torres, Susan J., and Caryl A. Nowson, 2007, Relationship between stress, eating behavior, and obesity, *Nutrition* 23, 887–894.

van der Cruijsen, Carin, Lola Hernandez, and Nicole Jonker, 2017, In love with the debit card but still married to cash, *Applied Economics* 49, 2989–3004.

Velde, François R., 2009, Chronicle of a deflation unforetold, *Journal of Political Economy* 117, 591–34.

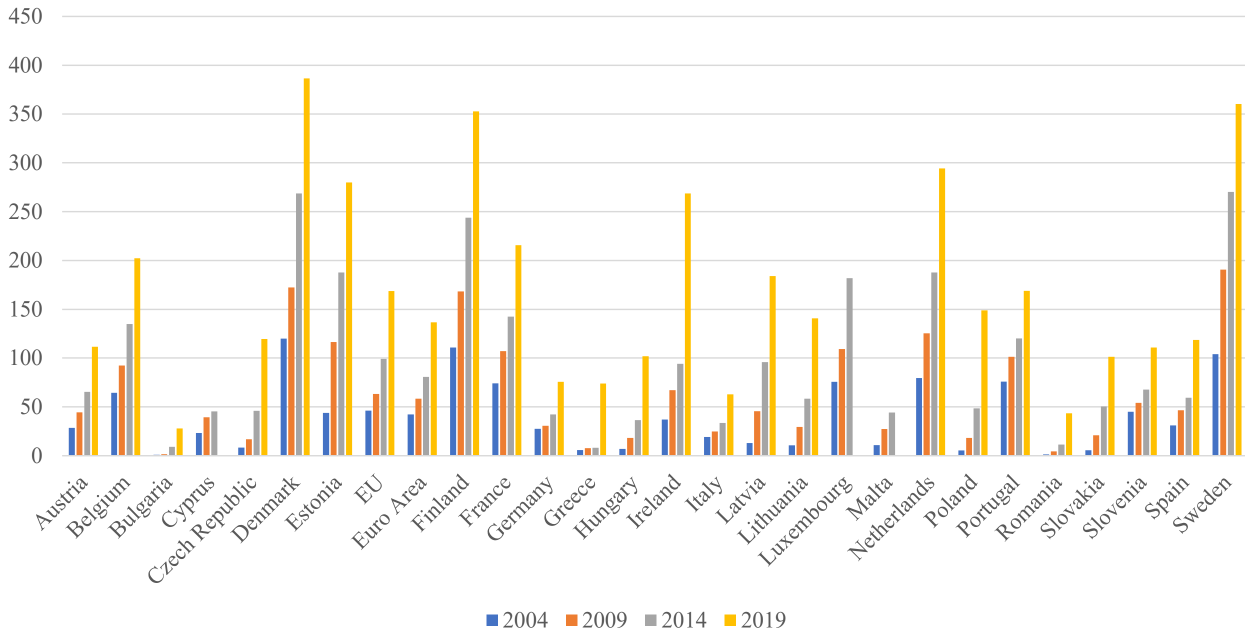
von Kalckreuth, Ulf, Tobias Schmidt, and Helmut Stix, 2014a, Choosing and using payment instruments: Evidence from German microdata, *Empirical Economics* 46, 1019–1055.

von Kalckreuth, Ulf, Tobias Schmidt, and Helmut Stix, 2014b, Using cash to monitor liquidity: Implications for payments, currency demand, and withdrawal behavior, *Journal of Money, Credit and Banking* 46, 1753–1785.

Yang, Botao, and Andrew T. Ching, 2014, Dynamics of consumer adoption of financial innovation: The case of ATM cards, *Management Science* 60, 903–922.

Figures and tables

Figure 1: Prevalence of card payments in Europe



Number of card transactions per inhabitant and year. Source: ECB.

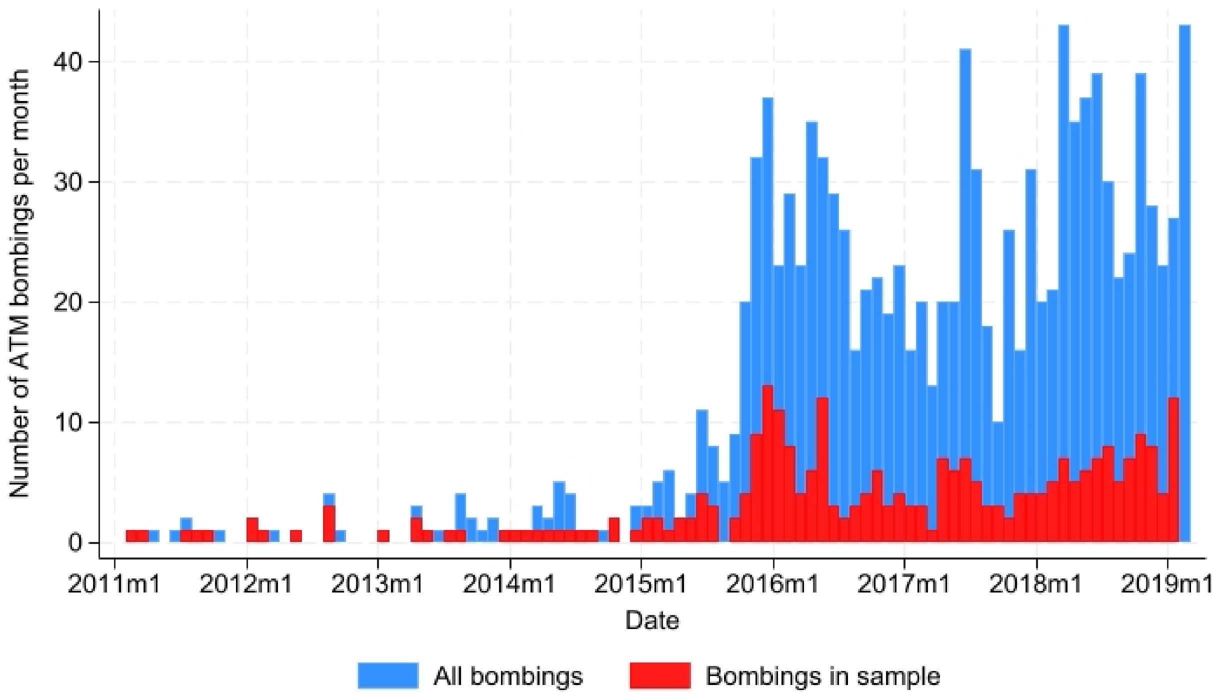
Figure 2: Exemplary explosive attacks on ATMs in Germany

(a) Destruction caused by explosive attacks on ATMs

(b) Modus operandi of perpetrators

Figure (a) shows the destruction caused by exemplary explosive attacks on ATMs (Sources: Verlag Dierichs GmbH & Co KG, Märkischer Zeitungsverlag GmbH & Co. KG, Allgäuer Zeitungsverlag GmbH, SWR, Landeskriminalamt Baden-Württemberg). Figure (b) shows the usual modus operandi of perpetrators (Source: FUNKE Mediengruppe).

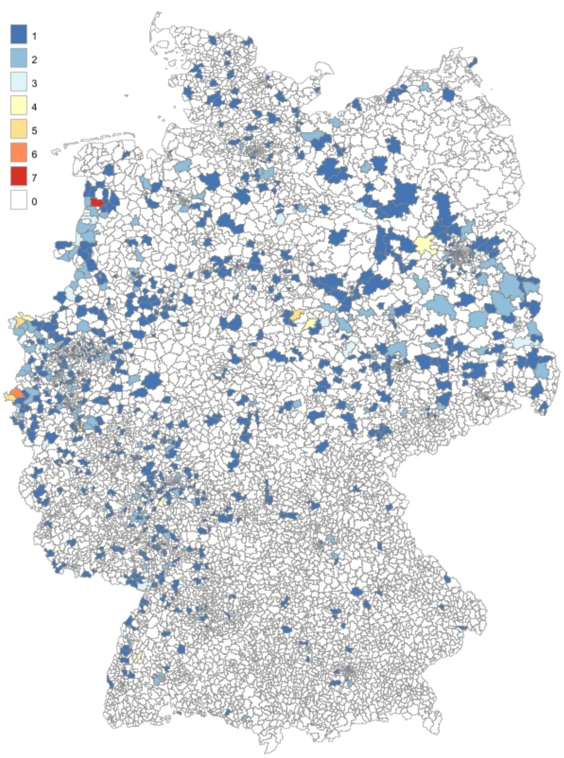
Figure 3: Explosive attacks on ATMs in Germany over time



This figure shows the number of explosive attacks in Germany from 2015 to March 2019. The bars in blue depict all ATM bombings reported to German police, while the red bars indicate the occurrence of ATM bombings in our final regression sample.

Figure 4: Geographical distribution of explosive attacks on ATMs in Germany

(a) Number of all explosive attacks on ATMs between January 2011 and March 2019



(b) Treated and control zip codes

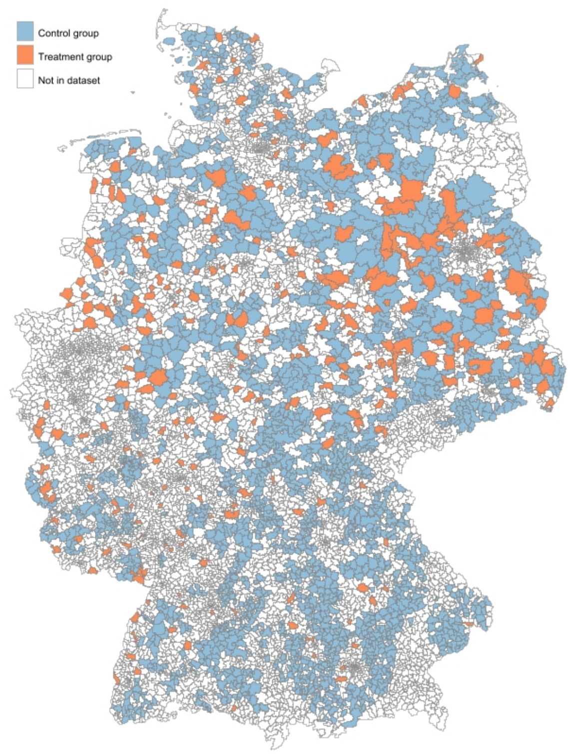
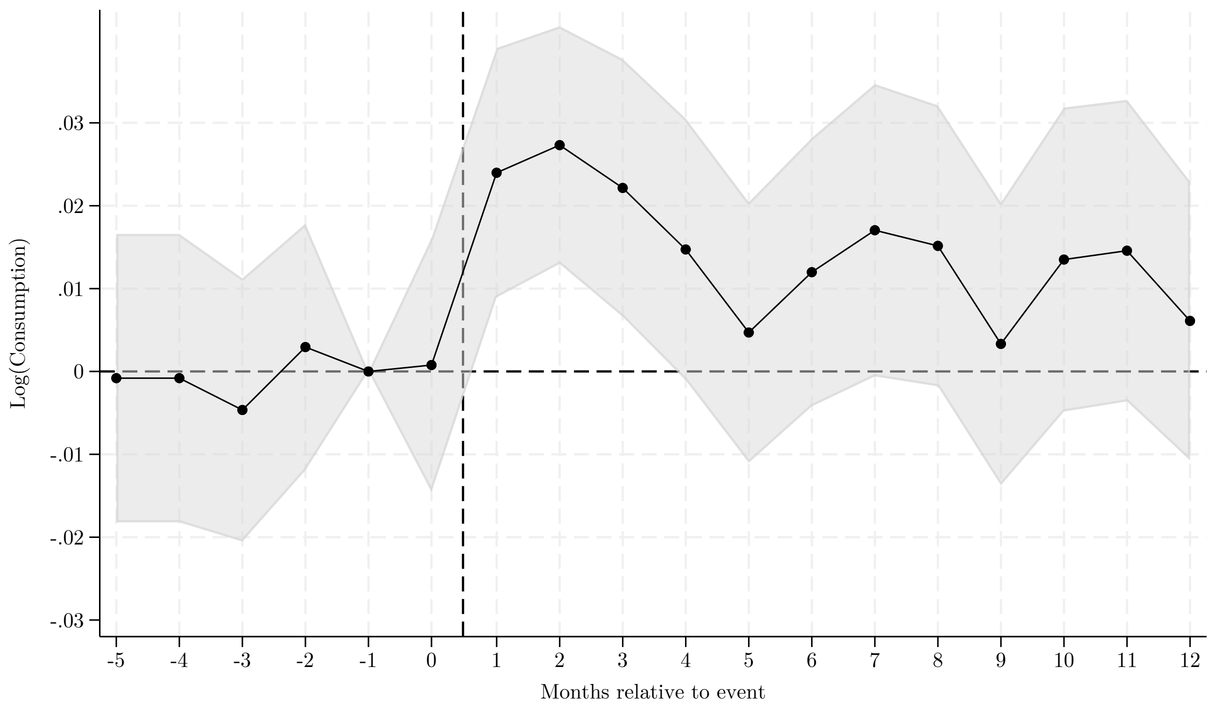


Figure (a) shows the number of explosive attacks on ATMs per ZIP code area in Germany from January 2011 to March 2019, while Figure (b) shows the distribution of treatment and control ZIP code areas.

Figure 5: Consumption around explosive attacks on ATMs



This figure shows the results of an OLS regression of the natural logarithm of total consumption (in €) per shopping trip on interactions of the treatment indicator with relative time dummies. The unit of observation is a shopping trip. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. The omitted category are shopping trips in the $[-60d, -30d]$ window before an ATM bombing, denoted by $t = -1$. The shaded area indicates 90% confidence intervals. The regression includes household $\times$ event, event $\times$ date, and household $\times$ shop fixed effects. Standard errors are clustered by event.

Table 1: Explosive ATM attacks

This table presents descriptive statistics for 275 explosive attacks on automated teller machines (ATMs) in Germany from January 2011 to March 2019. The first row displays the distribution of explosive attacks across ATM networks (Cash group: Deutsche Bank, Commerzbank, Postbank, Hypovereinsbank; Cash Pool: Sparda-Bank, Oldenburgische Landesbank, Other: Cashpoint, NoteMachine). The remaining rows show the average number of ATMs per ZIP code, both for all banks and for those within the same ATM network, the distance to the nearest ATM (in kilometers), and the percentage of restored ATMs. The last set of rows reports the distance to the closest store by store type (in kilometers). All distance measures are trimmed at the 99% percentile to alleviate the effect of outliers on the average distance.

			By ATM network					
	Obs.	All events	Sparkasse	Volksbank	Cash Group	Cash Pool	Other	NA
Number of Events	275		76	56	53	15	5	70
Treated ZIP characteristics								
Number of ATMs	268	8.58	8.15	7.06	11.57	10.53	8.20	7.52
Number of ATMs in same network	200	3.47	5.10	1.54	3.87	1.20	-	-
Treated ATM characteristics								
Distance to closest ATM [kilometer]	119	5.51	4.46	6.05	2.83	12.13	-	-
ATM restored [%]	202	63.86	76.71	60.78	52.08	93.33	-	27.27
Distance to closest store [kilometer]								
Supermarket	126	2.67	4.22	2.81	1.53	0.62	3.82	1.24
Discounter	127	3.24	5.89	3.02	1.61	0.70	1.94	1.95
Drug store	126	4.88	7.00	6.87	1.40	1.79	5.11	3.13
Department store	114	10.76	12.21	13.04	6.87	9.51	11.88	6.20

Table 2: Pre-treatment characteristics

This table compares mean characteristics of treated and control shopping observations in the month before an explosive attack on an ATM. The unit of observation is a shopping trip. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. T-statistics are based on standard errors clustered by event. Normalized differences follow Imbens and Wooldridge (2009). Values of less than 0.25 are considered not significantly different from zero. All consumption-related variables are trimmed at the 1st and 99th percentile.

	Treatment	Control	Diff.	t	Normalized Diff.	Obs.
Trip characteristics						
Consumption per trip	23.51	23.79	-0.28	-0.49	-0.01	25,850
Price per item	1.53	1.63	-0.10	-3.07	-0.05	25,850
Number of products	19.92	19.70	0.23	0.46	0.01	25,850
Household characteristics						
Monthly consumption per capita	92.04	92.51	-0.48	-0.30	-0.01	25,850
Monthly number of shop trips	10.10	10.30	-0.20	-0.88	-0.02	25,850
Monthly number of shop days	4.48	4.33	0.15	1.53	0.03	25,850
Household size						
Single	0.25	0.22	0.02	2.25	0.04	25,850
Couple	0.44	0.42	0.02	1.47	0.03	25,850
Three and more	0.32	0.36	-0.04	-3.39	-0.07	25,850
Income [€]						
500-1499	0.26	0.23	0.03	2.13	0.04	25,850
1500-2999	0.48	0.48	0.00	0.19	0.00	25,850
3000+	0.26	0.29	-0.03	-2.21	-0.05	25,850
Age						
20-39	0.24	0.25	-0.01	-0.63	-0.01	25,850
40-60	0.43	0.46	-0.03	-2.17	-0.04	25,850
60+	0.32	0.29	0.04	2.97	0.05	25,850
Zip code characteristics						
Population [10k]	2.03	1.45	0.58	7.53	0.42	25,850
Population density [Indiv. per qkm]	559.34	306.34	253.01	2.80	0.19	25,850
ATM per 10k person	5.40	5.66	-0.26	-1.57	-0.07	24,652
Purchasing power ['000€]	24.96	25.01	-0.41	-0.28	-0.01	25,850
Crimes per 10k person	587.42	539.15	48.27	3.02	0.15	25,850
Number of shops per 10k person						
Discounter	2.47	2.26	0.22	3.20	0.12	25,850
Supermarket	1.61	1.68	-0.07	-1.24	-0.05	25,850
Department store	0.21	0.12	0.09	3.91	0.23	25,850
Drug store	0.72	0.57	0.15	4.11	0.19	25,850
Number of HH	1,673	8,775				
Number of Events	275	275				

Table 3: Consumption around explosive attacks on ATMs

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. The unit of observation is a shopping trip within the time windows indicated in the column titles. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) [-90,30]	(2) [-90,60]	(3) [-90,90]	(4) [-90,180]	(5) [-90,240]	(6) [-90,360]
Treated × Post	0.023***	0.023***	0.023***	0.016***	0.016***	0.014***
	(2.79)	(3.73)	(3.96)	(3.01)	(3.22)	(2.72)
Obs.	984,648	1,218,082	1,447,082	2,112,254	2,537,595	3,356,896
Nr. of HH	9,545	9,559	9,567	9,573	9,573	9,575
Nr. of Treated HH	1,568	1,571	1,572	1,573	1,573	1,574
Nr. of Events	275	275	275	275	275	275
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Treatment intensity

This table shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Models 1 to 3 split the sample according to the availability of alternative ATMs operated by the same ATM network as the treated ATM in the treatment ZIP code area, while Models 4 to 6 examine the driving distance from the treated ATM to the next-best ATM. Models 1 and 4 replicate the baseline analysis from Model 3 in Table 3, but restrict the sample to events with available information on the treated ATM network (Models 1 to 3) or the exact address of the treated ATM (Models 4 to 6)). In Models 4 to 6, we split the sample by the median distance to an alternative ATM of the same network. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Alternative available			Distance to alternative		
	(1) All	(2) Yes	(3) No	(4) All	(5) Low	(6) High
Treated × Post	0.017***	0.014*	0.028**	0.025***	0.022**	0.030**
	(2.72)	(1.86)	(2.32)	(3.22)	(2.18)	(2.40)
Obs.	1,048,539	716,107	328,444	674,600	339,270	332,146
Nr. of HH	7,743	6,402	3,672	6,059	3,978	3,903
Nr. of Treated HH	1,138	840	299	661	385	276
Nr. of Events	200	134	66	119	60	59
Adj. R-squared	0.49	0.49	0.49	0.48	0.48	0.48
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Consumption: Robustness

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Compared to Table 3, Models 1 and 2 include fewer fixed effects. Model 3 adds control variables. Model 4 excludes local shops. Model 5 only looks at events for which the bombed ATM was eventually restored. Model 6 excludes shops offering point-of-sales cash withdrawals ("cash at till"). The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	No Shop x HH FE	Plus Shop FE	Plus Controls	Excl. local shops	Only restored ATMs	Cash at till unavailable
Treated × Post	0.015**	0.016***	0.023***	0.020***	0.017**	0.023***
	(2.37)	(2.72)	(4.00)	(3.28)	(2.14)	(2.92)
Obs.	1,460,373	1,460,373	1,447,082	1,200,823	688,443	797,535
Nr. of HH	9,721	9,721	9,567	9,529	6,525	8,818
Nr. of Treated HH	1,586	1,586	1,572	1,568	789	1,455
Nr. of Events	275	275	275	275	129	275
Adj. R-squared	0.26	0.35	0.49	0.47	0.49	0.51
Controls	No	No	Yes	No	No	Yes
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	No	No	Yes	Yes	Yes	Yes
Shop FE	No	Yes	No	No	No	No

Table 6: Number of products and price per item

This tables shows the results of OLS regressions the natural logarithm of the average price per item (Models 1 to 3) and of the natural logarithm of the number of items per shopping trip (Models 4 to 6). The unit of observation is a shopping trip within the time windows indicated in the column titles. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption-related variables are trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	ln(Price per product)			ln(Number of products)		
	(1) [-90,30]	(2) [-90,60]	(3) [-90,90]	(4) [-90,30]	(5) [-90,60]	(6) [-90,90]
Treated × Post	0.018***	0.014***	0.016***	0.005	0.009	0.007
	(3.82)	(3.43)	(4.03)	(0.59)	(1.49)	(1.14)
Obs.	984,648	1,218,082	1,447,082	984,648	1,218,082	1,447,082
Nr. of HH	9,545	9,559	9,567	9,545	9,559	9,567
Nr. of Treated HH	1,568	1,571	1,572	1,568	1,571	1,572
Nr. of Events	275	275	275	275	275	275
Adj. R-squared	0.44	0.44	0.44	0.56	0.57	0.57
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Consumption by product type

Models 1 and 2 show the results of Poisson regressions of the amount spent on branded and private label products. Models 3 and 4 show the results of Poisson regressions of the amount spent on temptation goods and all other products, respectively. Models 5 and 6 show the results of Poisson regressions of the amount spent on products on sale and non-sales products, respectively. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption-related variables are trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Temptation goods	Non-temptation goods	Brand	Private label	Sale	Non-sale
Treated × Post	0.028*	0.018***	0.025***	0.008	0.008	0.020***
	(1.96)	(3.70)	(3.94)	(1.13)	(0.65)	(3.83)
Obs.	1,262,571	1,446,711	1,444,074	1,241,271	1,405,854	1,446,430
Nr. of HH	9,373	9,567	9,561	9,469	9,512	9,566
Nr. of Treated HH	1,542	1,572	1,572	1,558	1,563	1,572
Nr. of Events	275	275	275	275	275	275
Pseudo R-squared	0.32	0.42	0.45	0.49	0.28	0.43
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Consumption by shop type

This tables shows the results of OLS regressions of the likelihood of a shop visit (Panel A) and the natural logarithm of total consumption (Panel B). In Panel A, the dependent variables are dummies set to 1 if a trip relates to the shop type in the column title, and 0 otherwise. Panel B restricts the observations to trips to the respective shop type listed in the column titles. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption-related variables are trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Extensive Margin				
	(1) Discounter	(2) Drug Store	(3) Local shop	(4) Supermarket	(5) Dep. Store
Treat. × Post	-0.008**	-0.000	0.001	0.006**	0.001
	(-2.59)	(-0.03)	(0.71)	(2.39)	(0.44)
Obs.	1,460,373	1,460,373	1,460,373	1,460,373	1,460,373
Nr. of HH	9,721	9,721	9,721	9,721	9,721
Nr. of Treated HH	1,586	1,586	1,586	1,586	1,586
Nr. of Events	275	275	275	275	275
Adj. R-squared	0.20	0.06	0.16	0.19	0.26
Household × Event FE	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes
	Panel B: Intensive Margin				
	(1) Discounter	(2) Drug Store	(3) Local shop	(4) Supermarket	(5) Dep. Store
Treat. × Post	0.014	0.040	0.027	0.025*	0.031*
	(1.58)	(1.31)	(1.53)	(1.67)	(1.73)
Obs.	632,665	77,812	237,762	326,940	140,979
Nr. of HH	8,827	5,126	6,032	7,589	4,899
Nr. of Treated HH	1,414	759	911	1,141	831
Nr. of Events	275	271	275	275	263
Adj. R-squared	0.37	0.35	0.35	0.40	0.46
Household × Event FE	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes

Table 9: Development of the effect over time

This tables shows the results of OLS regressions of consumption on interactions of the treatment indicator with relative time dummies. Model 1 examines the natural logarithm of total consumption (in €) per shopping trip, while Models 2 and 3 look at the number of products and the average price per product, respectively. The unit of observation is a shopping trip. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. The omitted category are shopping trips in the $[-60d, -30d]$ window before an ATM bombing, denoted by $t = -1$. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Consumption	(2) Number of products	(3) Price per product
Treated × Days: -180, -91	-0.001	-0.005	0.004
	(-0.14)	(-0.78)	(1.00)
Treated × Days: 0, 90	0.023***	0.008	0.015***
	(4.10)	(1.40)	(4.10)
Treated × Days: 91, 180	0.009	0.005	0.004
	(1.49)	(0.74)	(1.07)
Treated × Days: 181, 270	0.010	0.009	0.002
	(1.45)	(1.20)	(0.42)
Treated × Days: 271, 360	0.010	0.008	0.001
	(1.49)	(1.11)	(0.21)
Treated × Days: 361, 450	0.012	0.007	0.004
	(1.44)	(0.82)	(0.65)
Treated × Days: 451, 540	0.008	0.009	0.002
	(0.93)	(1.03)	(0.42)
Obs.	5,294,844	5,294,529	5,293,595
Nr. of HH	10,232	10,233	10,235
Nr. of Treated HH	1,663	1,662	1,664
Nr. of Events	275	275	275
Adj. R-squared	0.48	0.56	0.42
Household × Event FE	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes

Table 10: Individual heterogeneity

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Models 1 and 2 (3 and 4) divide the sample into two groups using a median split based on household income (age) as observed in the month prior to treatment. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Income		Age	
	$\leq 2,499$	$\geq 2,500$	≤ 54	≥ 55
Treated × Post	0.017**	0.029***	0.013	0.031***
	(2.25)	(2.92)	(1.26)	(3.84)
Obs.	821,113	620,937	663,716	778,844
Nr. of HH	5,593	4,558	6,087	3,757
Nr. of Treated HH	943	628	850	720
Nr. of Events	275	275	275	275
Adj. R-squared	0.50	0.47	0.50	0.47
Household × Event FE	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes

Table 11: Geographic heterogeneity

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Panels A and B split the sample into tertiles according to the treatment ZIP code area's average purchasing power and the share of financial products purchasing power. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. All models include household × event, event × date, and household × shop fixed effects. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Purchasing power		
	(1)	(2)	(3)
	1. Tertile	2. Tertile	3. Tertile
Treated × Post	0.020*	0.018**	0.030***
	(1.99)	(1.99)	(2.89)
Obs.	481,144	483,492	475,813
Nr. of HH	4,062	4,834	4,449
Nr. of Treated HH	575	517	482
Nr. of Events	85	100	90
Adj. R-squared	0.51	0.49	0.47
Household × Event FE	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes
	Panel B: Share of financial products purchasing power		
	(1)	(2)	(3)
	1. Tertile	2. Tertile	3. Tertile
Treated × Post	0.013	0.023**	0.030***
	(1.19)	(2.08)	(3.49)
Obs.	481,180	483,991	475,286
Nr. of HH	4,073	4,940	4,639
Nr. of Treated HH	466	523	585
Nr. of Events	91	90	94
Adj. R-squared	0.51	0.49	0.48
Household × Event FE	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes

Table 12: Payment choice around explosive attacks on ATMs

This tables shows the results of OLS regressions of payment choice. The dependent variable is a dummy set to 1 for card transactions, and 0 otherwise. The unit of observation is a financial transaction within the time windows indicated in the column titles. Treated transactions are conducted by households located within a district with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for transactions after an ATM attack, and 0 otherwise. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) [-1800,180]	(2) [-1800,180]	(3) [-1800,180]	(4) [-1800,360]	(5) [-1800,360]	(6) [-1800,360]
Treated × Post	0.072**	0.066***	0.050***	0.111***	0.086***	0.081***
	(2.389)	(3.334)	(2.907)	(4.578)	(4.120)	(3.231)
Treated	-0.013	-0.022	-0.020	-0.013	-0.017	-0.016
	(-0.860)	(-1.521)	(-1.261)	(-0.860)	(-1.118)	(-1.000)
Post	-0.083***	-0.002	0.038***	-0.104***	-0.016	0.019
	(-5.902)	(-0.223)	(3.293)	(-10.410)	(-1.350)	(1.244)
Observations	46,284	45,511	44,690	59,974	57,127	56,145
Adj. R-squared	0.009	0.138	0.236	0.009	0.133	0.240
Event × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Spending place FE	No	Yes	Yes	No	Yes	Yes
Weekday FE	No	Yes	Yes	No	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Transaction size FE	No	No	Yes	No	No	Yes

Appendix

Table A1: Product category expenditure share in YouGov Panel and German CPI Basket

This table compares the expenditure share of different product categories in the YouGov Panel to the German CPI Basket. We report the expenditure share of CPI product categories covered in the YouGov Panel and the expenditure shares in the full CPI basket. In the latter, we omit categories that are not covered in the YouGov Panel (e.g., housing, utilities, services, or hospitality).

		German CPI Basket	
Product Category	YouGov	Share Covered Basket	Share Full Basket
Food	74.7	46.9	
Bread and cereal products	10.5	8.3	1.9
Meat and fish products	16.8	11.8	2.6
Dairy products and eggs	11.7	7.9	1.8
Edible fats and oils	2.2	1.5	0.3
Fruit	5.6	5.2	1.2
Vegetables	7.0	6.2	1.4
Sugar, jam, honey and other sweets	5.6	3.6	0.8
Food, n.e.c.	15.4	2.6	0.6
Non-alcoholic beverages	8.0	6.4	
Coffee, tea and cocoa	2.8	1.9	0.4
Mineral water, lemonade and juices	5.1	4.5	1.0
Alcoholic beverages	6.3	7.1	
Spirits	1.4	1.5	0.3
Wine	2.0	3.1	0.7
Beer	2.9	2.5	0.6
Tobacco products	0.0	8.7	1.9
Goods and services for household management	3.3	4.8	
Consumables for household management	3.3	2.6	0.6
Services from domestic personnel	0.0	2.2	0.5
Other goods for leisure and garden, pets	1.9	9.7	
Goods for sport, camping and recreation	0.0	1.9	0.4
Garden products, plants and flowers	0.0	3.7	0.8
Pets, including consumables	1.9	3.0	0.7
Veterinary and other services for pets	0.0	1.0	0.2
Printed products, writing and drawing materials	1.6	6.8	
Books	0.0	1.8	0.4
Newspapers and magazines	1.6	2.5	0.6
Other printed products	0.0	1.4	0.3
Stationery and drawing materials	0.0	1.1	0.2
Personal care	4.2	9.6	
Hairdressing and other personal care services	0.0	4.6	1.0
Electrical devices for personal care	0.0	0.2	0.0
Other articles and products for personal care	4.2	4.8	1.1
Total	100	100	22.3

Table A2: Alternative sample definitions

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Compared to Table 3, Models 1 to 3 add bombings events during the COVID-19 pandemic to the sample. Models 4 to 6 look at an extended treatment sample by adding ZIP code areas within 5 kilometers of the ZIP code area with a bombed ATM. The unit of observation is a shopping trip within the time windows indicated in the column titles. Except for Models to 5, treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Incl. Covid			Treatment group: 0-5km		
	(1) [-90,30]	(2) [-90,60]	(3) [-90,90]	(4) [-90,30]	(5) [-90,60]	(6) [-90,90]
Treated × Post	0.015**	0.016***	0.014***	0.006	0.009*	0.009*
	(2.10)	(2.84)	(2.75)	(0.92)	(1.74)	(1.95)
Obs.	1,389,348	1,709,563	2,021,858	1,171,525	1,449,402	1,721,207
Nr. of HH	12,907	12,926	12,941	11,253	11,268	11,276
Nr. of Treated HH	2,127	2,131	2,132	2,732	2,736	2,737
Nr. of Events	376	376	376	313	313	313
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49
Controls	No	No	No	No	No	No
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Alternative clustering

This tables shows the results of OLS regressions of the natural logarithm of total consumption (in €) per shopping trip. Model 1 repeats Model 3 in Table 3 and clusters the standard errors by bombing event. Model 2 (3) clusters the standard errors by bombing event and treatment ZIP code (household ZIP). Model 4 (5) clusters the standard errors only by household ZIP code (only by treatment ZIP code). The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Event	(2) Event × Treated ZIP	(3) Event × ZIP	(4) ZIP	(5) Treated ZIP
Treated × Post	0.023***	0.023***	0.023***	0.023***	0.023***
	(3.96)	(3.96)	(3.91)	(4.04)	(3.96)
Obs.	1,447,082	1,447,082	1,447,082	1,447,082	1,447,082
Nr. of HH	9,567	9,567	9,567	9,567	9,567
Nr. of Treated HH	1,572	1,572	1,572	1,572	1,572
Nr. of Events	275	275	275	275	275
Adj. R-squared	0.49	0.49	0.49	0.49	0.49
Household × Event FE	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	No	No	No	No	No

Table A4: Number of shop trips

This table shows the results of Poisson regressions of the monthly number of shop trips. The unit of observation is a consumer-month within the time windows indicated in the column titles, conditional on the consumer reporting at least one shopping trip in a given month. The treatment group are households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for months after an ATM attack, and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) [-3,1]	(2) [-3,2]	(3) [-3,3]	(4) [-3,6]	(5) [-3,9]	(6) [-3,12]
Treated × Post	-0.001	-0.001	-0.001	0.002	0.003	0.003
	(-0.04)	(-0.10)	(-0.16)	(0.33)	(0.47)	(0.40)
Obs.	113,448	134,749	155,590	215,864	273,375	323,496
Nr. of Households	9,545	9,547	9,551	9,554	9,554	9,556
Nr. of Events	275	275	275	275	275	275
Pseudo R-squared	0.50	0.49	0.49	0.48	0.48	0.48
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Coarsened exact matching: Pre-treatment characteristics

This table compares mean characteristics of treated and control shopping observations in the month before an explosive attack on an ATM. The unit of observation is a shopping trip. Treated and control shopping trips are selected based the coarsened exact matching algorithm described in Section 3.3. T-statistics are based on standard errors clustered by event. Normalized differences follow Imbens and Wooldridge (2009). Values of less than 0.25 are considered not significantly different from zero. All consumption-related variables are trimmed at the 1st and 99th percentile.

	Treatment	Control	Diff.	t	Normalized Diff.	Obs.
Trip characteristics						
Consumption per trip	23.22	23.19	0.04	0.06	0.00	12,821
Price per item	1.55	1.63	-0.08	-1.97	-0.04	12,821
Number of products	19.87	19.02	0.85	1.41	0.03	12,821
Household characteristics						
Monthly consumption per capita	90.66	92.92	-2.26	-1.14	-0.02	12,821
Monthly number of shop trips	9.95	10.32	-0.37	-1.36	-0.03	12,821
Monthly number of shop days	4.41	4.31	0.10	0.88	0.02	12,821
Household size						
Single	0.25	0.23	0.01	1.03	0.02	12,821
Couple	0.43	0.41	0.02	1.27	0.03	12,821
Three and more	0.32	0.36	-0.03	-2.14	-0.05	12,821
Income [€]						
500-1499	0.26	0.22	0.04	2.68	0.07	12,821
1500-2999	0.48	0.47	0.02	0.99	0.02	12,821
3000+	0.25	0.31	-0.06	-3.41	-0.09	12,821
Age						
20-39	0.25	0.27	-0.02	-1.35	-0.03	12,821
40-60	0.44	0.45	-0.01	-0.74	-0.02	12,821
60+	0.32	0.29	0.03	2.11	0.05	12,821
Zip code characteristics						
Population [10k]	1.83	1.81	0.02	0.20	0.01	12,821
Population density [Indiv. per qkm]	558.08	571.04	-12.96	-0.09	-0.01	12,821
ATM per 10k person	5.54	5.68	-0.14	-0.68	-0.04	12,232
Purchasing power	24.76	25.32	-0.56	-3.26	-0.19	12,821
Crimes per 10k person	586.27	531.77	54.50	2.47	0.19	12,821
Number of shops per 10k person						
Discounter	2.56	2.27	0.28	3.41	0.19	12,821
Supermarket	1.65	1.71	-0.07	-0.94	-0.05	12,821
Department store	0.21	0.15	0.06	2.16	0.14	12,821
Drug store	0.73	0.71	0.02	0.41	0.02	12,821
Number of HH	1,350	4,680				
Number of Events	240	240				

Table A6: Coarsened exact matching: Regression results

This tables shows the results of OLS regressions of consumption. Model 1 examines the natural logarithm of total consumption (in €) per shopping trip, while Models 2 and 3 look at the number of products and the average price per product, respectively. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated and control shopping trips are selected based the coarsened exact matching algorithm described in Section 3.3. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. Standard errors are clustered by event. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) ln(Consumption)	(2) ln(Number of products)	(3) ln(Price per item)
Treated × Post	0.020***	0.003	0.017***
	(2.82)	(0.42)	(3.72)
Obs.	714,884	714,884	714,884
Nr. of HH	5,494	5,494	5,494
Nr. of Treated HH	1,259	1,259	1,259
Nr. of Events	240	240	240
Adj. R-squared	0.51	0.58	0.47
Household × Event FE	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes

Table A7: Consumption: Product categories

This table shows the results of Poisson regressions of the amount spent on a certain product category in case the category was included in a shopping trip. The unit of observation is a shopping trip within three months before and three months after a bombing event. Treated shopping trips are conducted by households located within a ZIP code area with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. Post is set to 1 for shopping trips after an ATM attack, and 0 otherwise. Consumption is trimmed at the 1st and 99th percentile. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Beverages	(2) BHC	(3) Confect-ionary	(4) Food	(5) Fresh food	(6) Near food
Treated × Post	0.013	-0.002	0.013	0.028***	0.021***	0.035*
	(0.90)	(-0.09)	(0.78)	(3.75)	(3.16)	(1.79)
Obs.	1,293,793	1,061,444	1,257,735	1,358,650	1,351,189	1,175,975
Nr. of HH	9,442	8,840	9,315	9,516	9,538	9,108
Nr. of Treated HH	1,557	1,448	1,533	1,563	1,569	1,495
Nr. of Events	275	275	275	275	275	275
Pseudo R-squared	0.35	0.51	0.31	0.39	0.35	0.38
Household × Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Event × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Shop FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A8: Pre-treatment characteristics: Bundesbank survey

This table compares mean characteristics of treated and control households before an explosive attack on an ATM. The unit of observation is a shopping trip. Treated shopping trips are conducted by households located within a district with an explosive attack on an ATM, while the control group consists of households at least 10 kilometers (but not more than 50 kilometers) away from the treated area. For the treatment group, there are ten or less ZIP code areas within each district. T-statistics are based on standard errors clustered by event. Normalized differences follow Imbens and Wooldridge (2009). Values of less than 0.25 are considered not significantly different from zero. All consumption-related variables are trimmed at the 1st and 99th percentile.

	Treatment	Control	Diff.	t	Normalized Diff.	Obs.
Transaction characteristics						
Cash transaction	0.83	0.80	0.02	1.03	0.04	45,395
Card transaction (excl. credit cards)	0.12	0.14	-0.01	-1.03	-0.03	45,395
Card transaction (incl. credit cards)	0.13	0.15	-0.01	-0.96	-0.03	45,395
Transaction amount	20.85	22.03	-1.18	-1.31	-0.04	43,975
Household characteristics						
High education	0.22	0.25	-0.02	-0.77	-0.04	5,113
Income [€]						
Below 1000	0.43	0.38	0.05	1.40	0.07	5,114
1000-1999	0.39	0.39	0.00	-0.04	0.00	5,114
2000+	0.18	0.23	-0.05	-1.44	-0.08	5,114
Age	46.61	47.52	-0.91	-0.89	-0.04	5,112
Married	0.47	0.50	-0.03	-0.70	-0.05	5,114
Household size	2.32	2.21	0.11	1.38	0.07	5,113
Female	0.54	0.54	-0.01	-0.21	-0.01	5,114
District characteristics						
Population [10k]	14.29	38.53	-24.24	-11.29	-1.07	5,114
Population density	1047.69	1083.13	-35.43	-0.18	-0.03	5,114
ATM per 10k person	3.39	3.20	0.18	1.32	0.16	5,114
GDP per capita	31.13	33.90	-2.77	-1.44	-0.17	5,114
Number of ZIP code areas	7.97	16.22	-8.25	-8.59	-0.71	5,114
Number of HH	240	2,010				
Number of Events	27	41				