Card-Sales Response to Merchant Contactless Payment Acceptance[1]

David Bounie[2] and Youssouf Camara[3]

August 25, 2020

Abstract

Disruptive innovations in digital payments are happening in a large number of countries around the world. In this paper, we investigate how merchants' acceptance of a contactless card technology affects card sales. Using score matching and difference-in-difference techniques on a unique sample of about 275,580 merchants in France, we find that accepting contactless payments in 2018 increases the card-sales amount by 15.3 percent on average (and by 17.1 percent the card-sales count) compared to merchants who do not accept contactless payments. We also find evidence that accepting contactless payments exerts a positive spillover of about 1.3 percent in the amount of contact card sales, and thus significantly increases the average annual card-sales amount and count for small merchants and new entrepreneurs.

Keywords: Card acceptance, contactless cards, digital payments, difference-in-difference.

JEL Classifications: C21, E21, E42, O33.

[1]We would like to thank Ludovic Francesconi, Leo Van Hove, John Galbraith, Katérina Levallois, Loys Moulin, Marianne Verdier, and Samuel Willy for their helpful comments on earlier versions of the paper, as well as seminar participants to the AFREN workshop in Paris. This research has been conducted within the Research Chair "Digital Finance" under the aegis of the Risk Foundation, a joint initiative by Groupement des Cartes Bancaires CB, La Banque Postale, Telecom Paris and University of Paris 2 Panthéon-Assas.

[2]i3, CNRS, Telecom Paris, Institut Polytechnique de Paris; Email: david.bounie@telecom-paris.fr.

[3]i3, CNRS, Telecom Paris, Institut Polytechnique de Paris; Email: yocamara@telecom-paris.fr.

1 Introduction

New cashless payment technologies have emerged around the world especially in Asia and Europe. Propelled by innovative banks and financial technology companies (called Fintech), digital payments have become a strong alternative to cash and cheques, which are still widely used in developed countries, and their use is becoming increasingly popular. According to the European Central Bank (2018), for instance, the total number of non-cash payments in the EU increased by 7.9% to 134 billion in 2017 compared to the previous year.

Contactless payment cards are one of the latest innovations in digital payments. At the beginning of 2010s, major banks in France decided to issue contactless payment cards with the national card scheme, Cartes Bancaires CB[1]. Contactless payments allow customers to pay by tapping their cards or mobile phones directly onto a contactless-enabled terminal, processing the payment in a few seconds. Contactless technologies are a faster alternative to contact card payments (by inserting the card in the terminal), and possibly to other payment instruments like cash as well. Contactless payments by cards are capped at EUR 30 (since October 2017), whereas there is no limit for mobile phones; in this case customers are simply required to put in their mobile code to authorise the payment. Contactless payments in France are mainly done by cards and aimed at competing with cash that is mainly used to purchase small-value items. According to the latest statistics provided by CB, 2.1 billion of contactless payments were carried out in 2018 for a total amount of EUR 22.5 billion (CB, 2018). As of December 2018, one in five card payments are made using contactless cards in France.

France is not a unique case. In the euro zone, Esselink and Hernandez (2017) show that almost 10% of all point-of-sale transactions in 2016 in the Netherlands are paid using contactless cards, followed by Slovakia, Austria and Belgium with respective percentages of 4.3%, 2.5%, and 1.8%. In Canada, Henry et al. (2018) find that the usage of contactless payment cards has increased substantially; over half of the transaction volumes of both debit cards and credit cards is contactless. Similarly, a recent report from the Federal Reserve Bank of Boston outlines the rapid uptake of contactless payment cards in Australia, New Zealand, and Switzerland,

[1] We use the abbreviation 'CB' to indicate the source of the card payments.

and reports that when three key elements are in place – broad acceptance, issuance, and consumer demand – mass adoption is more likely to occur (Crowe and Tavilla, 2019).

Although there is increasing economic literature on payment instruments, there are still few empirical papers that examine the relation between the merchant acceptance of a new payment technology and its business sales.[2] The objective of this paper is to investigate the causal effect of accepting contactless payments on the annual merchant card sales (amount, count, and average transaction amount). Three main questions motivate the analysis: What is the impact of contactless cards on merchant card sales? How does the merchant card acceptance change the way consumers use their payment instruments at point of sale, and do we observe a substitution between contact and contactless card technologies? Is the impact the same according to sectors (e.g. restaurants, and hotels), and the size of the merchant (small versus large merchants)?

To answer these questions, we use a unique sample of about 275,580 unique CB merchants[3] in France, and we use score matching and difference-in-difference methods to compare changes in the businesses that have adopted contactless payments in 2018 to similar businesses that still do not accept contactless payments. We find that the merchants who started accepting contactless payments experience an average increase of 15.3 percent in the annual card-sales amount, and 17.1 percent in sales count, relative to their counterparts who do not accept. Accepting contactless payments therefore drives card business growth. We also find evidence that accepting contactless payments has a positive spillover effect on the annual card-sales amount of about 1.3 percent, but a negative effect in the upper parts of the contact card-sales amount distribution (75th and 90th percentiles). Moreover, the benefits of acceptance are larger for small merchants. For example, the average card-sales amount of merchants with annual card sales that are less than EUR 25,000 increases by 34.9 percent, while the average card-sales amount for large retailers (more than EUR 500,000) increases by 10.3 percent. Unsurprisingly, we find that the bene-

[2]There is an extensive literature on technology acceptance (see among others Davis, 1989; Venkatesh et al., 2003; Hall and Khan, 2003; C. Srivastava et al., 2010; Gerhardt Schierz et al., 2010), technology diffusion (Caselli and Coleman, 2001; Rogers, 2003; Comin and Hobijn, 2004) and payment choice (Bounie et al., 2016; Ching and Hayashi, 2010; Wang and Wolman, 2016).

[3]Only aggregated data related to CB card transactions performed by CB merchants have been used.

fits of accepting contactless payments are the largest for bakeries (32.8 percent) that typically sell small-value items and need to speed up transactions during peak hours. Finally, we also highlight that the spillover effect is much stronger for new entrepreneurial firms who have just started their business (14 percent).

This paper contributes to the economic literature on payment instruments by estimating the causal impact of the merchant acceptance of a new contactless payment technology on the annual card sales (amount, count, and average transaction amount), and how the impact changes with the business size (small, medium and large retailers), the business sector, the company's age, and the use of other accepted payment technologies (e.g. contact cards). In recent years, a growing body of the economic literature has focused on consumer adoption and usage of payment instruments (see, for example, Stavins, 2018), and on merchant acceptance (Arango et al., 2015, Bounie et al., 2017 and Jonker, 2011). Most of these studies use survey data and standard correlation models to study the impact of existing payment technologies (e.g. such as standard debit and credit cards) or new payment technologies (e.g. mobile and contactless cards) on paper-based payment instruments (e.g. cash or cheques). Trütsch (2014), for example, examines the impact of contactless payments on the spending ratio between debit and credit cards payments and all other payment methods. Using a national survey on consumer payment behavior in the US in 2010, the author shows that contactless payments increase the spending ratio at the point-of-sale for both debit and credit cards payment. Fung et al. (2012) use the 2009 Bank of Canada Method of Payment survey to measure the impact of contactless credit cards on cash usage. They find evidence that the use of contactless credit cards reduces on average the total value and volume of cash usage.

Agarwal et al. (2019) is the closest paper to our research. Using a difference-in-difference setting, they investigate the effect of a new mobile-payment technology (QR code) adoption in Singapore by comparing two groups of merchants who have already adopted the technology, small merchants and large ones. Merchants are all clients of the same bank in Singapore. They find a positive impact of mobile payment technology on promoting business growth, especially among small merchants. As Agarwal et al. (2019), our paper is one of the first contributions to the literature on the effects of financial technologies (Fintech) on the real economy (Zhang et al., 2019). However, it differs from their approach on two crucial points. First, we provide a comparison between a group of merchants who have adopted the new payment technology and a group that did not adopt the technology. Second, we have information on all the CB card sales for each CB merchant as we have data from all CB card scheme banks members in France. The quality of the data provides a good representation of all merchants in France and not the merchants of a particular bank that might have singular economic characteristics.

The remainder of the paper is structured in five sections. Section 2 describes the French card market. Section 3 presents a simple framework to discuss how contactless card technologies may affect merchant card sales, and also provides details on the methodology and the estimation strategy. Section 4 examines the estimation results and finally, Section 5 concludes.

2 The French Card Market at a Glance

France is a country with a mature card market. Cartes Bancaires CB is one of the leading card schemes. Cartes Bancaires CB was created by the French banks which, in 2018, accounted for more than 100 French and foreign members (payment service providers, banks and e-money institutions) operating in France, 1.77 million CB merchants, 70.4 million CB cardholders. This has amassed more than 12.7 billion CB transactions and EUR 593 billion (CB, 2018).[4]

The term ”CB” refers to all cards that carry the CB brand. CB cards can be “immediate” debit cards, and deferred debit cards (“charge cards” that require the balance to be paid in full each month), and even “real” credit cards (cards with a credit line). A peculiarity of the French card market is that merchants who accept CB cards will make no distinction between debit cards and the other types. Therefore, a CB merchant is a merchant affiliated to the CB scheme and a CB transaction is a card transaction performed under the CB brand.

Since 2012, the CB banks have issued massive amounts of cards with contactless technology in addition to standard contact technology. Contactless cards use the Near Field Communication (NFC) technology that allow cards (or mobile) and a

[4]Cardholder is the term used to refer to the user of a card. The number of cardholders affiliated to a domestic card scheme such as CB can be greater than the number of people living in a country because a person may hold several cards for example.

payment terminal to communicate wirelessly to each other when they are very close together under certain security conditions. NFC is in fact a subset of a technology called RFID (Radio-frequency Identification), a technology that enables identification devices through radio waves.[5]

Between 2015 and 2018, the development of contactless card technology in France was among the main goals of the French national strategy related to non-cash payments designed by the Ministry of Finance and Public Accounts, the Ministry of Economy, Industry, and Digital Affairs, and the Banque de France. This strategy was divided into two focal points. First, by default, all newly installed card payment terminals had to be equipped with the contactless technology. Second, consumers had to be systematically informed and consent to having their new cards equipped with contactless technology as well as the terms and conditions for using such cards.[6] This strategy led to the rapid increase of card payment terminals equipped with the new contactless technology in France.

At the end of 2014, 45.9 percent of CB cards, i.e. 27.5 million contactless CB cards, and 19.7 percent of CB merchants were equipped with the CB contactless technology; overall, 64.5 million contactless CB transactions for a total amount of EUR 706.5 million were recorded by CB. Three years later, at the end of 2017, 71 percent of CB cards and 44 percent of CB merchants were contactless, for a total activity of about 1.2 billion contactless CB transactions and EUR 12.4 billion. Finally, in 2018, the French contactless market was launched indefinitely with 76 percent of contactless CB cards and 59 percent of contactless CB merchants, and with 2.1 billion contactless CB transactions for EUR 22.5 billion were registered.

3 Framework, Data and Estimation Strategy

In this section, we investigate the causal effect of contactless payments on merchant card sales (amount, count and amount per transaction). First, we use a very simple framework to discuss how contactless card technologies may affect merchant card sales. Second, we briefly present the data. Third, we describe in detail the

[5]NFC technology allows secure data to be exchanged within 10 cm. Egger (2013) provides an overview of the NFC technology and its applications in the tourism industry.

[6]For more details, see the document entitled National Strategy on Means of Payment, 2015-2018.

standard difference-in-difference method that we use to compare the changes in the average (quantile) card sales between the CB merchants who have accepted the contactless payments in 2018 (the "treatment group"), and the CB merchants who do not still accept contactless payments in 2018 (the "control group").

3.1 Merchant Card Sales and Contactless Payments Acceptance: A Simple Framework

We provide a simple framework to study how the merchant card sales may change after the acceptance of the contactless card technology, and also substitution as well as complementarity effects between contact and contactless card technologies.

Suppose that at time t, two payment technologies are available on the market: technology 1 is a contact card technology denoted cc, and technology 2 is a non card technology denoted nc (such as cash and cheque). The total sales of merchant i at time t, $\pi_{i,t}$, is then composed of sales from technology 1, $\pi^{cc}_{i,t}$, and sales from technology 2, $\pi^{nc}_{i,t}$.[7] At time $t+1$, a new contactless card technology denoted cl is adopted by merchant i. The total sales of merchant i at time $t+1$ after the adoption of the new technology is thus:

$$\tilde{\pi}_{i,t+1} = \tilde{\pi}^{nc}_{i,t+1} + \tilde{\pi}^{cc}_{i,t+1} + \tilde{\pi}^{cl}_{i,t+1}.^{8} \tag{1}$$

Note that in the absence of technology adoption, the total sales of merchant i at time $t+1$ would have been:

$$\pi_{i,t+1} = \pi^{nc}_{i,t+1} + \pi^{cc}_{i,t+1}. \tag{2}$$

Following equations (1) and (2), the adoption of a contactless card technology by merchant i may affect its total sales for two reasons. First, the acceptance of a new payment technology may attract new customers who will use the new card technology (Agarwal et al., 2019). Second, long-term and loyal customers may also use the payment instruments differently, for example by replacing contact card or non-card payments with contactless card payments. Let $\tilde{\pi}^{*}_{i,t+1} \geq 0$ denote the change

[7]Index i allows the sales to depend on several merchant characteristics, such as its sector of activity and its location.

[8]$\tilde{\pi}$ indicates the sales of merchant i after the adoption of the new technology.

of the total sales resulting from the adoption of the contactless card technology and defined as follows:

$$\tilde{\pi}^{*}_{i,t+1} = \tilde{\pi}^{nc}_{i,t+1} - \pi^{nc}_{i,t+1} + \tilde{\pi}^{cc}_{i,t+1} - \pi^{cc}_{i,t+1} + \tilde{\pi}^{cl}_{i,t+1}. \quad (3)$$

Equation (3) can be used to analyze the impact of the adoption of contactless cards on card sales, and possible substitution effects between card payment technologies. Firstly, if $(\tilde{\pi}^{cc}_{i,t+1} + \tilde{\pi}^{cl}_{i,t+1}) - (\pi^{cc}_{i,t+1}) > 0$, then the sales from contact and contactless card technologies are higher than those that would have resulted without the adoption of the new payment technology. The adoption of the contactless payment technology therefore increases the card sales for the merchant by attracting new customers, encouraging consumers to use card technologies more intensively, or by displacing non-card payments.

Secondly, if $\tilde{\pi}^{cc}_{i,t+1} - \pi^{cc}_{i,t+1} > 0$, then the adoption of a contactless card technology spills over contact card payments, and the positive externality implies higher contact card sales. However, if $\tilde{\pi}^{cc}_{i,t+1} - \pi^{cc}_{i,t+1} < 0$, a negative externality occurs, and the merchants will gain lower sales from contact card payments. Therefore, there is a cannibalization between contact and contactless card payments. Merchants still gain from the adoption of contactless payments if contactless card sales offset those of contact card payments, and possibly also the sales of non card payments.

3.2 Sample Design

Thanks to a research partnership with Cartes Bancaires CB, we have access to a unique data set of merchant card activities from 2015 to 2018. Cartes Bancaires CB collects the amount and count for every CB merchant associated with their merchant business identification number, creation date,[9] activity type (offline/online business), and geographical location. However, for the purposes of clarifying the context of our study, it is worth noting that, before 2018, payment service providers had no obligation to separately report contact and contactless payments to Cartes Bancaires CB. This is why we measured the impact of contactless payments from 2018 onwards.[10]

[9]The creation date of the merchant corresponds to the first card transaction date registered in the CB system.

[10]Nevertheless, we will use data from 2015 to 2017 to check a crucial assumption of the difference-in-difference estimation, that is the common trend evolution of sales before the contactless payment acceptance by the treatment group.

To investigate the causal effect of contactless payments on merchant card sales, we focus the analysis on merchants who decided to accept contactless payments in 2018 and who did not accept contactless payments in 2017 (the "treatment group"). We then compare this group to merchants who did not yet accept contactless payments in 2018, and therefore who did not accept contactless payments in 2017 (the "control group").

As we consider 2018 as the treatment period, we therefore exclude the merchants who already accepted contactless payments in 2017 from the sample. We also exclude the online CB merchants who do not use contactless payments from the sample, and also vending machines. The remaining sample includes 346,240 unique offline CB merchants, with 72,571 in the treatment group and 273,669 in the control group. Finally, as we want to estimate the counterfactual and verify that the control and treatment groups had the same evolution of average card sales before the acceptance of contactless payments, we keep all the businesses that have existed since at least 2015 in the sample, and exclude the others. After this step, we are left with 275,580 businesses: 57,830 in the treatment group and 217,750 in the control group.

Merchants who accept contactless payments are not directly comparable to those who do not. Merchants decide when to adopt the new payment technology, thereby making the acceptance of contactless payments a non-random experiment. To avoid possible selection bias, we first use a score matching setting to compare merchants who are similar in all relevant pre-treatment characteristics. The contactless payment acceptance may depend on merchant characteristics and on city characteristics. For example, a merchant may be more willing to accept contactless payments as the number of cardholders and contactless payments in the city is high (network externalities). In the following section, we will match merchants with both types of observable characteristics, and we will use a difference-in-difference setting to remove unobserved heterogeneity.

3.3 Score Matching

Inferring the impact of acceptance of contactless payments on merchant card sales involves speculation on how this merchant would have performed had he or she not accepted contactless payments. To estimate the effect of such a treatment, i.e. accepting contactless payments, Rosenbaum and Rubin (1983) proposed a framework called *propensity score matching* or simply score matching. Score matching is a straight-forward statistical matching technique to obtain unbiased estimation of causal treatment effects by adjusting for the covariate confounding. Based on the observable characteristics of two groups, the control and the treatment group, it is possible to estimate the counterfactual, i.e. the situation that would have prevailed in the absence of the treatment. In short, score matching attempts to replicate the properties of a randomized trial by creating a sample of units that received the treatment that is comparable on all observed covariates to a sample of units that did not receive the treatment.

We use score matching to match merchants in the control group to merchants in the treatment group such that the effect of the treatment can be estimated from the resulting matched sample. To do that, we use a standard logistic regression to estimate the probability that a merchant i adopts the contactless technology conditional on pre-treatment characteristics. The probability of accepting the contactless technology ($score_i$) can be written as follows:

$$Score_i = P(Treated_i = 1|X_i) = \frac{exp(f(X_i))}{1 + exp(f(X_i))}, \tag{4}$$

with X_i the vector of observable characteristics at the levels of the merchant and its city. The merchant characteristics include the sector of activity[11], the age of business (plus the age squared), a dummy variable indicating whether the merchant has employees, a categorical variable of 16 classes representing the number of employees (from 1 employee to more than 10,000 employees), the volume of card transactions, the card-sales growth rate, the average card transaction value, and the number of bank accounts. The merchant city characteristics include the geographical location,[12] the population, the share of contactless payments and the number of NFC equipped merchants.[13] $f(X)$ is a linear combination of variables in X_i.

Using the *caliper matching* (Raynor, 1983 and Dehejia and Wahba, 2002), each NFC equipped merchant is then assigned a twin of the control group. In other words,

[11]We use the Nomenclature des Activites Francaises (NAF) provided by the National Institute of Statistics (INSEE) to classify the business sectors.

[12]Geographical location is defined by the longitude and latitude of the merchant's city.

[13]We use observable characteristics for 2017; we also perform the test with 2016 and obtain similar results.

we select an untreated merchant who has the closest score to a treated merchant. Formally, merchants i and j are matched under the condition that $\min_j |Score_i - Score_j| < h$, with i a merchant of the treatment group, j a merchant of the control group, and h the tolerable maximum score distance between i and j.[14] As is standard in the literature, we use $h = 0,02$.[15]

Score matching is based on two main assumptions. The first is the *conditional independence assumption (CIA)* or *unconfoundedness assumption* that relies on the sufficient existence of observable variables for which an independence of treatment assignment can be verified.[16] The second assumption named *common support assumption (or overlap assumption)* refers to a common region where the distribution of propensity scores of the treatment and control groups are the same. The common support assumption ensures that merchants with the same X_i have positive probability of both accepting and not accepting contactless payments such that $Score_i \in]0,1[$. An important step is therefore to check the region of common support between treatment and control groups. Among the several ways suggested in the literature, the most straightforward one is a visual analysis of the density distribution of the propensity score in both groups (Caliendo and Kopeinig, 2008). We will use this approach in the next sections.

3.4 Difference-In-Difference Method

To difference out remaining heterogeneity, we use a difference-in-difference estimation strategy on the matched sample (Heckman et al., 1997).[17] The difference-in-difference setting ties well to our case in that we compare the evolution of the average sales (amount, count and amount per transaction) of the treatment group before and after treatment (denoted ATT for Average Treatment effect on the Treated) to that of the control group.

The difference-in-difference estimator assumes that in the absence of the treat-

[14] Merchant j is drawn with replacement. It can be paired with different merchants in the treatment group.

[15] For more details about the tolerance level, see Smith and Todd (2005).

[16] The conditional independence assumption cannot be directly tested.

[17] There are a great deal of papers that use the difference-in-difference method to estimate the effect of a program (see Bertrand et al. (2004), Hastings (2004), Gaynor et al. (2013), Greenstone and Hanna (2014), Schmeiser et al. (2016), Bose and Das (2017), Dague et al. (2017), Zimmerman (2019), Cengiz et al. (2019) among others).

ment the average sales of the two groups would have changed in the same way (*common trend assumption*). Consequently, any difference observed after the treatment could only come from the acceptance of contactless payments. The common trend assumption can be verified by plotting the evolution of the average sales of the two groups before the treatment.

However, as the Average Treatment effect on the Treated (ATT) only captures the impact on the average card sales, and not the impact on the entire distribution, we will also measure the quantile treatment effect on the treated (denoted QTT). QTT more precisely describes the impact of the treatment on the merchants' card sales than ATT. It models the entire conditional sales distribution. With the difference-in-difference method, the q-th QTT corresponds to the difference between the evolution of q-th quantile of the treatment group's sales before and after program, and the equivalent quantile of the other group.

In quasi-experiments, when there is a self-selection, conventional quantile regression methods are not adapted to correctly estimate QTT (Koenker and Bassett, 1978). In fact, QTT cannot be measured by comparing the quantile of the sales of the two groups before and after the intervention. Several methods have been developed to control this type of unobserved heterogeneity (Athey and Imbens, 2006; Firpo, 2007; Lamarche, 2010; Fan and Yu, 2012; Callaway et al., 2018). Firpo (2007) proposes a method for estimating QTT subject to observable characteristics. This method is based on identification assumptions comparable to those found in score matching methods. This method is implemented using standard quantile regressions, weighting the observations by the estimated weight corresponding to the propensity score. We estimate QTT by considering the method developed by Firpo (2007).[18]

We can write the model for estimating ATT and QTT on the matched sample as:

$$log(Y_{i,t}) = \beta_0 + \beta_1 \cdot \mathbb{1}(T=1) + \beta_2 \cdot \mathbb{1}(t=2018) + \beta_3 \cdot \mathbb{1}(t=2018) \cdot \mathbb{1}(T=1) + \epsilon_{i,t}, \text{[19]} \quad (5)$$

[18]It is worth noting that there is no trend assumption to estimate QTT. Using the Firpo strategy, the only one assumption is to weigh variables by the probability of being treated. We use the strategy in Callaway et al. (2018) for the purpose of robustness (see Appendix).

[19]ATT (QTT) represent the average (quantile) card-sales response to the contactless technology adoption in 2018. ATT can be written as: $ATT = \beta_3 = [\mathbb{E}(log(Y)|T=1, t=2018) - \mathbb{E}(log(Y)|T=$

with $log(Y_{i,t})$, the log of annual total sales amount (or count, or amount per transaction) of merchant i at time t. The dummy variable $\mathbb{1}(T=1)$ is equal to one if the merchant i belongs to the treatment group (i.e accepts the contactless payments) and captures constant differences in composition between the two groups (group fixed effect). The dummy variable $\mathbb{1}(t=2018)$ is equal to one (or zero) for the contactless card acceptance period in 2018 (if t=2017) (time fixed effect). On the matched sample, using a linear regression, β_3 corresponds to the average treatment effect for the treated (ATT); while using quantile regression with the Firpo (2007) strategy, it represents the quantile treatment effect for the treated (QTT).

4 Estimation Results

In this section, we first discuss the impact of the acceptance of contactless cards on merchant card sales, and then how it changes with the size of the merchant, the sector, the date of creation of the business, and finally how it spills over other payment instruments. We perform additional tests in the Appendix to study the robustness of the results.

4.1 Causal Impact on Merchant Card Sales

Here, we investigate whether the acceptance of contactless payments directly affects merchant card sales. Following Equation (3) in particular, we expect a positive and significant effect on card sales if merchants attract new consumers that use contactless payments or if older consumers replace non-card payments by card payments, especially contactless payments.

To estimate the average (and quantile) card-sales response to the merchant adoption of contactless payment technology, we first use the score matching method described in Section 3.3, and check whether there is a region of common support between treatment and control groups. Overall, 57,813 merchants in the treatment

$1, t=2017))] - [\mathbb{E}(log(Y)|T=0, t=2018) - \mathbb{E}(log(Y)|T=0, t=2017)]$. Similarly, the q-th QTT can be written as: $QTT_q = \beta_3 = [Q_q(score * log(Y)|T=1, t=2018) - Q_q(score * log(Y)|T=1, t=2017)] - [Q_q(score * log(Y)|T=0, t=2018)) - Q_q(score * log(Y)|T=0, t=2017)]$ where $score$ represents the probability of being treated conditional on the observable characteristics (see equation (4)).

group are paired,[20] and Figure 1 confirms the existence of a region of common support, and then the possibility of using the matched sample for an estimation.

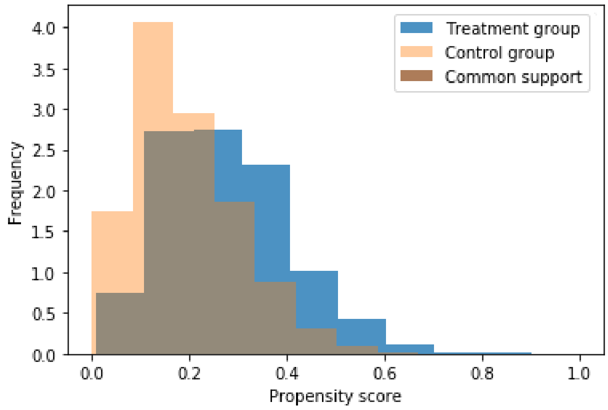


Figure 1: Region of Common Support

To further check the robustness of the score matching, we have also computed the mean statistics of observable characteristics of the treatment and control groups. In theory, we should no longer observe any statistical significant differences between both groups. Table 1 confirms this expected result and shows that we have a panel of reasonably balanced and homogeneous treatment and control merchants. Overall, after matching, the differences between the treatment and control groups in the observable merchant and his city characteristics are not statistically different from zero.[21] This analysis allows us to use a difference-in-difference setting to identify the card-sales response to merchant contactless acceptance.[22]

[20] After matching, we have 57,813 merchants in the treatment group and the same number in the control group. As we observe these two groups over the two time periods, 2017 and 2018, then we have 231,252 observations.

[21] We note in Table 1 that the average transaction value is significantly different in the control and the treatment groups after matching (two euros). A possible explanation of the difference can be due the fact that, at the time of the matching, the merchants adopting the contactless payment technology are those already carrying out low-value transactions, whereas the merchants in the control group are still predominantly represented by merchants carrying out larger-value transactions.

[22] As it is standard in the literature (see for example Agarwal and Qian (2014) and Agarwal et al. (2015)), we can use a difference-in-difference setting on the overall matched sample, but also on sub-samples of merchants (e.g. merchant sectors and merchant sizes). In the following sub-sample analyses, we also checked the quality of both groups. In doing this, we applied the matching score for each case and verified that the identifying assumptions of matching (common support assumption) and difference-in-difference (common trend assumption) are not violated. The results are similar and available upon request.

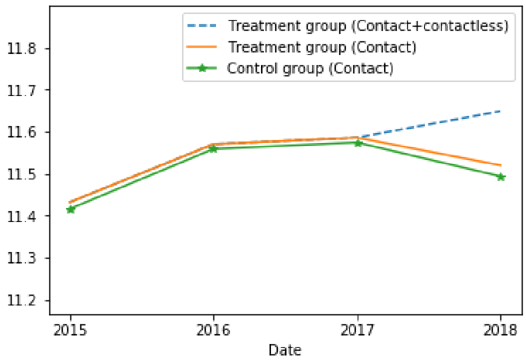
Table 1: Summary statistics of the treatment and control groups before and after score matching

	Treatment group		Control group			Matched treatment group		Matched control group		
	Mean	SD	Mean	SD	Diff.	Mean	SD	Mean	SD	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Merchant characteristics										
Age	9.17	5.25	8.76	5.29	-0.41***	9.17	5.25	9.16	5.26	-0.01
Number of bank accounts	1.22	0.47	1.16	0.41	-0.06***	1.22	0.47	1.22	0.5	0.0
Growth rate	0.02	0.38	0.0	0.4	-0.02***	0.02	0.38	0.02	0.32	0.0
Transaction volume	7654.43	38377.3	3667.74	17643.2	-3986.69***	7612.82	37644.5	7468.19	41382.8	-144.63
Average transaction value	77.29	100.44	124.47	322.88	47.18***	77.29	100.45	79.29	118.36	2.0***
Business sectors										
Bakery	0.02	0.02	0.01	0.01	-0.01***	0.02	0.02	0.02	0.02	0.0
Food	0.03	0.03	0.02	0.02	-0.01***	0.03	0.03	0.03	0.03	0.0
Health	0.13	0.11	0.18	0.15	0.05***	0.13	0.11	0.13	0.11	0.0
Hotel	0.01	0.01	0.01	0.01	0.0	0.01	0.01	0.01	0.01	0.0
Leisure	0.04	0.04	0.03	0.02	-0.01***	0.04	0.04	0.04	0.04	0.0
Personal_care	0.09	0.08	0.07	0.07	-0.02***	0.09	0.08	0.08	0.08	-0.01***
Restaurant	0.16	0.13	0.09	0.08	-0.07***	0.16	0.13	0.15	0.13	-0.01***
Supermarket	0.03	0.03	0.02	0.02	-0.01***	0.03	0.03	0.03	0.03	0.0
Taxi	0.01	0.01	0.02	0.02	0.01***	0.01	0.01	0.01	0.01	0.0
Hiring=Yes	0.75	0.19	0.64	0.23	-0.11***	0.75	0.19	0.75	0.19	0.0
Number of employees										
1 to 2 employees	0.32	0.22	0.31	0.21	-0.01***	0.32	0.22	0.32	0.22	0.0
3 to 5 employees	0.21	0.17	0.17	0.14	-0.04***	0.21	0.17	0.21	0.17	0.0
6 to 9 employees	0.11	0.1	0.08	0.07	-0.03***	0.11	0.1	0.11	0.1	0.0
10 to 19 employees	0.06	0.06	0.04	0.04	-0.02***	0.06	0.06	0.06	0.06	0.0
20 to 49 employees	0.02	0.02	0.02	0.02	0.0	0.02	0.02	0.02	0.02	0.0
50 to 99 employees	0.0	0.0	0.01	0.01	0.01***	0.0	0.0	0.01	0.01	0.01***
More than 100 employees	0.01	0.01	0.01	0.01	0.0	0.01	0.01	0.01	0.01	0.0
Merchant city characteristics										
Localisation										
Longitude	2.54	8.46	1.64	13.55	-0.9***	2.54	8.46	2.55	8.55	0.01
Latitude	45.85	7.43	44.44	10.85	-1.41***	45.85	7.43	45.9	7.47	0.05
Population	45173.2	64847.4	47591.4	65040	2418.22***	45166.3	64824.9	44432.1	62676.3	-734.17*
Share of contactless payment	0.13	0.05	0.13	0.06	0.0	0.13	0.05	0.13	0.05	0.0
Share of NFC equipped merchants	0.51	0.11	0.49	0.13	-0.02***	0.51	0.11	0.51	0.11	0.0
Observations	57,830		217,748			57,813		57,813		

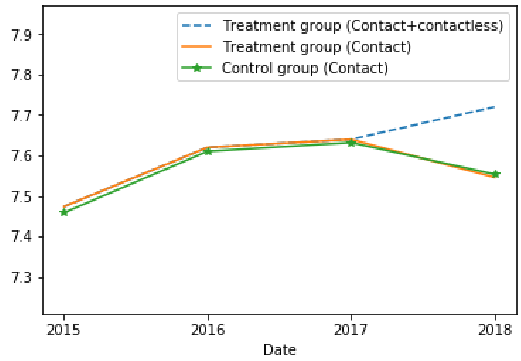
Notes: This table reports on the summary statistics of the treatment and control groups, both before and after score matching. The treatment sample consists of merchants who accept contactless payments in 2018, and the control sample represents all other merchants who still do not accept contactless payments. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

We finally use a difference-in-difference method on the matched sample to estimate the average (and quantile) treatment effect on the treated, ATT (and QTT). We first show that the common trend assumption is not violated and thus we can measure the causal effect of contactless card acceptance using the difference-in-difference method. Figure 2 precisely illustrates that the treatment and control groups have the same evolution of the average log of card-sales amount (a), sales count (b) and amount per transaction (c) before 2018 (period of contactless payment adoption).

(a) log (total sales amount)



(b) log (total sales count)



(c) log (amount per transaction)

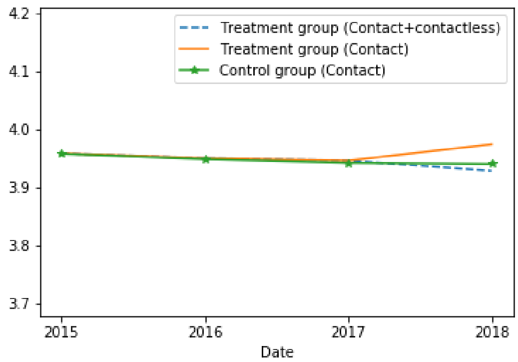


Figure 2: Test of Common Trend Assumption

Table 2 summarizes the estimation results. The intersection between row i and column j represents the average (or quantile) response of the column j to the acceptance of contactless payment technology.

First, we find that the merchants who decided to accept contactless payments in 2018, compared to those who had yet to do so, increase their annual card-sales amount by 15.3 percent.[23] The average sales count also increases by 17.1 percent. The effects are statistically significant at the 1 percent level. Accepting contactless payments therefore contributes to an increase in total card sales by attracting more consumers and/or by displacing non-card payments such as cash and cheque payments. Moreover, we note that the average amount per transaction decreases by 1.6

[23]The estimated ATT for log of card-sales amount on Table 2 is 0.142, which is equivalent to a percentage increase of 15.3 percent (= exp(0.142) − 1). All following ATT or QTT interpretations for log dependent variables will use the same formula.

percent: this result is in line with expectations as contactless cards are mainly used for small-value purchases (up to EUR 30).[24]

Table 2: Contactless Acceptance and Business Card Sales

		Log(Sales amount)	Log(Sales count)	Log(Amount per transaction)
		(1)	(2)	(3)
ATT		0.142***	0.158***	-0.016***
		(0.004)	(0.004)	(0.001)
	q=10	0.227***	0.215***	-0.023**
		(0.025)	(0.03)	(0.01)
	q=25	0.128***	0.144***	-0.016*
		(0.017)	(0.023)	(0.009)
QTT	q=50	0.094***	0.119***	-0.013**
		(0.016)	(0.02)	(0.007)
	q=75	0.083***	0.121***	-0.018*
		(0.019)	(0.022)	(0.01)
	q=90	0.061**	0.084***	-0.02*
		(0.024)	(0.025)	(0.011)
Observations			231,252	

Notes: This table reports on the average (and quantile) card-sales response of merchants who accept contactless payments in 2018 compared with matched merchants who do not accept contactless payments, ATT (and QTT). On the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT, and to QTT when using quantile regression. The dependent variable is the log of card-sales amount in column (1), the log of card-sales count in column (2) or the log of card amount per transaction in column (3). All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level (for ATT) and bootstrapped standard errors (for QTT) are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Second, another interesting question to address is the effect of contactless payments on business size. Do we observe differences between retailers of a similar, smaller, or larger size, and what is the magnitude of the impact? Contactless payments are indeed intended to speed up small-value transactions at the point-of-sale

[24] Another way to test the assumption of the common trend is to perform a ”placebo test”. We apply in Appendix the placebo test on the previous periods when there is no contactless card adoption. We do not expect to find any significant impact. For example, we do not find a significant effect of contactless card adoption in 2016 for the merchants who adopt the new technology in 2018.

in fast-paced environments where customers often have fewer cashier options. For smaller businesses, which can have high cashier turnover rates, streamlining transaction processes can lead to significant gains in efficiency and productivity as well as a reduction in the cash management burden and hassles from running out of change.

The quantile regressions in Table 2 show that the effect is indeed heterogeneous across the card sales distribution and benefits the smallest merchants. For example, the 10th percentile card-sales amount of merchants who accept contactless payments increases by 25.5 percent (p-value < 0.01) compared to merchants who do not accept contactless payments. However, in the middle and upper parts of the distribution, the effect decreases to reach 6.3 percent (p-value < 0.01) for the 90th percentile. This result is similar for the sales count.[25]

A possible explanation for this result could be due to the variety of retailer adoption strategies when incorporating contactless payment technology. Larger retailers may have embraced the technology from its launch in 2012 and thus benefited from the effects of the technology earlier in the adoption phase. As as result, by 2018, these larger retailers may have attracted fewer new customers. On the contrary, smaller retailers might have taken on contactless payments later on in the adoption phase, and, compared to those that had not yet adopted this approach, the smaller retailers might have attracted consumers who preferred to use contactless payments. To further investigate this reasoning, we define six categories of retailers, namely <EUR 25,000, EUR 25-50,000, EUR 50-100,000, EUR 100-200,000, EUR 200-500,000 and >EUR 500,000, and calculate the share of retailers equipped with the contactless payment technology in 2017 for each category. We observe that in 2017, 40% of smaller retailers (<EUR 25,000) adopted the contactless payment technology compared to 77% of larger retailers (>EUR 500,000).[26]

[25] To test the robustness of this result, we have defined six categories of retailers based on the card sales observed in 2017: <EUR 25,000, EUR 25-50,000, EUR 50-100,000, EUR 100-200,000, EUR 200-500,000 and >EUR 500,000. Estimation results confirm QTT regressions and show that accepting contactless payments allows the smallest merchants (less than EUR 25,000) to increase the average card-sales amount by 34.9 percent compared to merchants who do not still accept contactless payments, whereas the average benefits amounts to 10.3 percent for larger retailers (>EUR 500,000). For merchant card sales between EUR 25,000 and EUR 500,000, the estimated effects are between 10.4 percent and 16 percent.

[26] The share of retailers equipped in 2017 is between 55% and 65% for merchant card sales between EUR 25,000 and EUR 500,000. These descriptive statistics seem to support our intuitions.

4.2 Contact Cards Spillover Effects

An interesting related question is how the acceptance of a new payment technology impacts the use of other payment technologies already accepted by the merchant at point-of-sale. In particular, we are interesting in exploring how contactless payments carried out by cards spill over to contact card sales. Indeed, when a merchant accepts contactless payments, it might attract new customers who have a high preference for the card. Consumers use the contactless card for small payments for example in place of cash, but possibly also instead of the contact card. The number of contact card payments may then decrease if there is a substitution between the contactless card and the contact card for low-value payments. Similarly, when contactless cardholders are loyal, they can also use the contact card instead of cheques or cash for large-value amounts. In the end, compared to a merchant who has not yet adopted contactless payments, an equipped merchant can then record both a lower number of contact card payments and a higher amount of card payments.

To explore the question of spillover effects, we compare the contact card response of the treated merchants who accept contactless payments with those who do not accept contactless cards but contact cards. We follow the same methodology described in the previous section regarding the score matching and difference-in-difference settings. Table 3 summarizes and highlights the main results. We find evidence that the merchants who accept contactless payments experience an average increase of 1.3 percent in annual contact card-sales amounts but an average decrease in the number of contact card payments of 1.6 percent. Consequently, as the contact card is more often used to pay large-value purchases and less frequently used at the point-of-sale, the average amount per transaction increases by 2.9 percent. These results confirm the intuition described previously; the adoption of contactless payments can help attract new consumers who frequently use contactless cards for low-value purchases in place of contact cards, and contact cards for large-value purchases in place of alternative means of payment such as cheques.

Table 3: Contact Cards Spillover Effects

		Log(Sales amount)	Log(Sales count)	Log(Amount per transaction)
		(1)	(2)	(3)
ATT		0.013***	-0.016***	0.029***
		(0.004)	(0.004)	(0.001)
	q=10	0.075***	0.083***	0.038***
		(0.026)	(0.031)	(0.01)
	q=25	0.013	0.026	0.055***
		(0.017)	(0.022)	(0.009)
QTT	q=50	-0.026	-0.046**	0.043***
		(0.016)	(0.02)	(0.006)
	q=75	-0.042**	-0.101***	0.008
		(0.019)	(0.021)	(0.01)
	q=90	-0.061**	-0.133***	-0.01
		(0.024)	(0.025)	(0.011)
Observations			231,252	

Notes: This table illustrates the average (and quantile) contact card-sales response of merchants who accept contactless payments in 2018 compared to matched merchants who do not accept contactless payments, ATT (and QTT). On the matched merchants, using linear regression, β_3 of equation (5) corresponds to ATT, and to QTT when using quantile regression. The dependent variable is the log of the contact card-sales amount in column (1), the log of the contact card-sales count in column (2) or the log of the contact card amount per transaction in column (3). All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level (for ATT) and bootstrapped standard errors (for QTT) are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

However, surprisingly, the previous results do not hold for all the distribution of contact card sales. For example, although the spillover effect is positive for the 10th percentile (more contactless payments led to more contact card payments in count and value), the spillover effect is negative for the 75th and 90th percentiles (more contactless payments led to fewer contact card payments in count and value). Accepting contactless payments decreases by 4.1 and 5.9 percent the 75th and 90th percentiles contact card sales amount, respectively. These results therefore indicate that for large retailers, the contactless card is a substitute to the contact card for low-value amounts, and lowers the total contact card sales count and amount.

Moreover, as we note in Table 3, the average transaction amount of contact cards did not increase in 2018, and possibly suggests that after the adoption of contactless cards in 2018, the share of contact card transactions further shifted to smaller-value transactions.[27]

4.3 Card-Sales Response by Business Sector

The impact of contactless payments may vary among business sectors that are more concerned with limiting queues, saving time at the checkout, and enhancing the buying experience in stores. Some sectors are also more concerned with small-size transactions, the main target of contactless payments.

To capture heterogeneity between sectors, we use the statistical classification of business activities in force in France since 2008.[28] We focus particularly on nine categories: Bakery, Food, Health, Hotel, Leisure, Beauty care, Restaurant, Supermarket, and Taxi.[29] Table 4 displays the estimation results.[30] Unsurprisingly, the benefits of accepting contactless payments are the largest for bakeries that typically sell small-value items and need to speed up transactions during peak hours. Indeed the average benefits respectively increase by 32.8 percent[31] (card-sales amount) and 45.1 percent (card-sales count) for bakeries who have adopted contactless card payments compared with bakeries that do not. Estimation results also confirm a large and significant benefit for retailers in the Leisure sector (27.6 percent), as well as for taxis which shows a significantly higher increase in card-sales count (26.2 percent), and in card-sales amount (31.3 percent) relative to their counterparts.

[27] The benefits of accepting contactless cards are further strengthened by a positive spillover effect on contact card sales for small merchants. We indeed observe that the low-revenue merchants (<EUR 25,000) experience an average increase of about 12.3 percent in the annual contact card sales amount compared with merchants who do not accept contactless cards. This effect is not statistically significant for merchants with card sales between EUR 25,000 and EUR 200,000, but it is negative and significant at the 5 percent level for larger merchants (>EUR 200,000).

[28] The National Institute of Statistics (INSEE) uses the Nomenclature des Activites Francaises (NAF) to classify the business sectors.

[29] We use the following NAF codes: Restaurant (561XX and 563XX), Hotel (551XX and 552XX), Taxi (4932Z), Supermarket (471XX), Leisure (90XXX, 91XXX, 93XXX and 476XX), Health (862XX and 4773X), Bakeries (1071C, 1071D and 4724X), Beauty care (9602X and 9604X), and Food (4721X, 4722X, 4723X, 4725X and 4729X).

[30] We have checked for each case that the identifying assumptions of score matching and difference-in-difference are not violated.

[31] The estimated ATT for log of card-sales amount on Table 4 is 0.284, which is equivalent to a percentage increase of 32.8 percent ($= \exp(0.284) - 1$). All following ATT interpretations for log dependent variables will use the same formula.

Table 4: Average Card-Sales Response (ATT) by Business Sectors

	Bakery	Food	Health	Hotel	Leisure	Personal_care	Restaurant	Supermarket	Taxi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Log(Sales amount)				
ATT	0.284***	0.148***	0.073***	0.18***	0.244***	0.08***	0.204***	0.189***	0.233***
	(0.029)	(0.02)	(0.007)	(0.038)	(0.025)	(0.009)	(0.01)	(0.025)	(0.038)
					Log(Sales count)				
ATT	0.372***	0.158***	0.085***	0.232***	0.251***	0.083***	0.217***	0.223***	0.272***
	(0.031)	(0.019)	(0.006)	(0.038)	(0.024)	(0.009)	(0.01)	(0.025)	(0.036)
					Log(Amount per transaction)				
ATT	-0.088***	-0.01***	-0.012***	-0.052***	-0.007	-0.003**	-0.013***	-0.034***	-0.039***
	(0.006)	(0.003)	(0.002)	(0.015)	(0.006)	(0.001)	(0.002)	(0.005)	(0.012)
Observations	5,436	7,950	29,994	1,838	8,552	19,926	36,086	6,902	3,324

Notes: This table illustrates the average card-sales response to the adoption of contactless payments by business sector. For each business sector in columns (1)-(9), on the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT. The dependent variable is the log of the card-sales amount, sales count or amount per transaction. All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * and indicate significance at the 1%, 5% and 10% levels, respectively.

A further interesting question to investigate is the benefits of adopting contactless payments for small and large retailers in a given sector. Are there differences between business sectors? Estimation results indicate that the impact of the adoption of contactless payments in sectors that benefit most from it is the same regardless of the size of the business.[32] For example, in the case of bakeries or restaurants, the effect is roughly equivalent for the 25th and 75th percentiles card-sales amount. However, for the less responsive sectors like health, personal care, or food, the impact is only significant for the lowest percentiles card-sales amount (10th and 25th percentiles).

Finally, accepting contactless payments also exerts large positive and negative spillover effects on contact card payments that significantly vary according to sectors. For example, Table 5 shows that the leisure sector benefits the most from the adoption of contactless contact card activity; accepting contactless payments increases the average contact card-sales amount by almost 10.8 percent whereas they decrease by 14.7 percent in the taxi sector. The decline indicates a switch from contact card to contactless payments in taxis. Also interesting to note is the

[32]Due to space limitations, we do not report on all the results and Tables in the paper. However results can be provided upon request.

cannibalization effect in bakeries; accepting contactless payments, compared to merchants who do not, significantly decreases the sales count on average by 12 percent. Consumers therefore prefer to use their contactless card instead of their contact card to pay small-value items. This conclusion is also true for taxis who experienced a significant drop in the sales count (11 percent), indicating again a switch between contact and contactless payments.

Table 5: Spillover Effects and Average Contact Card-Sales Response (ATT) by Business Sector

	Bakery (1)	Food (2)	Health (3)	Hotel (4)	Leisure (5)	Personal_care (6)	Restaurant (7)	Supermarket (8)	Taxi (9)
	Log(Sales amount)								
ATT	-0.039	0.031	-0.014**	-0.092**	0.103***	0.012	-0.007	0.002	-0.159***
	(0.03)	(0.02)	(0.007)	(0.042)	(0.025)	(0.009)	(0.01)	(0.026)	(0.039)
	Log(Sales count)								
ATT	-0.128***	-0.028	-0.044***	-0.051	0.047*	-0.028***	-0.055***	-0.057**	-0.116***
	(0.032)	(0.02)	(0.007)	(0.04)	(0.024)	(0.009)	(0.01)	(0.026)	(0.037)
	Log(Amount per transaction)								
ATT	0.089***	0.059***	0.029***	-0.041**	0.056***	0.039***	0.048***	0.059***	-0.043***
	(0.006)	(0.003)	(0.002)	(0.017)	(0.006)	(0.001)	(0.002)	(0.005)	(0.013)
Observations	5,436	7,95	29,994	1,838	8,552	19,926	36,086	6,902	3,324

Notes: This table reports the average contact card-sales response to the adoption of contactless payments by business sector. For each business sector in columns (1)-(9), on the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT. The dependent variable is the log of the contact card-sales amount, sales count or amount per transaction. All the regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

4.4 New Entrepreneurs and Card-Sales Response by Merchant Age

In this section, we investigate whether the impact of contactless adoption on sales, count, and amount per transaction is affected by merchant's age. The intuition is simple: newly created businesses may have a particular appetite for new payment technologies that more established businesses do not have, attracting in turn a new clientele that is more familiar with new technologies. To test this assumption, we split merchants into four groups. The first group is called new entrepreneurs, and their age in the database is equal to one in 2017.[33] The second group is between 2 and 5 years old in 2017 (called young), the third between 6 and 10 years old (called medium), and the last more than 10 years old (called old).

Table 6 summarizes the estimation results. Specifically, we find evidence that merchant age is a strong factor in card-sales business. First, we observe that, in 2018, new entrepreneurs that adopted contactless payments increased their annual card-sales amount and count (27.1 and 30.3 percent, respectively)[34] compared to those which had not yet accepted contactless payments. Second, on average, the young merchants' card sales increased by 18.3 percent while those of the medium and old merchants increased by 15.6 and 13.9 percent, respectively. Interestingly, these observations are also related to the size of the merchants in each group. For example, we observe, in 2017, that half of the young merchants have less than EUR 81,600 for EUR 24,000 average card sales, while half of the old merchants have less than EUR 132,900 for 457,560 average card sales.

[33]As outlined in Section 3.2, the creation date of the merchant corresponds to the first card transaction date registered in the CB system. We then define a new entrepreneurial firm as a firm with the first sale happening in 2016, and apply the difference-in-difference method described in Section 3.4 for matched merchants existing at least during two full years, i.e. 2017 and 2018.

[34]The estimated ATT for log of card-sales amount of Table 6 is 0.24, which is equivalent to a percentage increase of 27.1 percent (= exp(0.24) − 1). All following ATT interpretations for log dependent variables will use the same formula.

Table 6: Average Card-Sales Response (ATT) by Merchant Age

	Merchants whose age is between			
	1 year	2-5 years	6-10 years	> 10 years
	(1)	(2)	(3)	(4)
	Log(Sales amount)			
ATT	0.24***	0.168***	0.145***	0.121***
	(0.016)	(0.011)	(0.01)	(0.009)
	Log(Sales count)			
ATT	0.265***	0.187***	0.156***	0.135***
	(0.016)	(0.01)	(0.01)	(0.009)
	Log(Amount per transaction)			
ATT	-0.025***	-0.02***	-0.011***	-0.015***
	(0.005)	(0.002)	(0.002)	(0.002)
Observations	21,616	101,086	85,580	122,462

Notes: This table reports the average card-sales response to the adoption of contactless payments by merchant age. For each merchant age in columns (1)-(4), on the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT. The dependent variable is the log of card-sales amount, sales count or amount per transaction. All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

In line with previous results, Table 7 confirms a strong positive spillover effect of adopting contactless cards for new entrepreneurs; sales increased by 9.4 percent following the acceptance of contactless payments compared to companies that did not accept contactless payments. The magnitude of this effect is much more prominent than the one observed in Section 4.2 for firms that were founded before 2015.

Table 7: Spillover Effects and Average Contact Card-Sales Response (ATT) by Merchant Age

	Merchants whose age is between			
	1 year	2-5 years	6-10 years	> 10 years
	(1)	(2)	(3)	(4)
	Log(Sales amount)			
ATT	0.09***	0.024**	0.018*	0.003
	(0.017)	(0.011)	(0.011)	(0.01)
	Log(Sales count)			
ATT	0.074***	-0.003	-0.019*	-0.025***
	(0.016)	(0.01)	(0.01)	(0.009)
	Log(Amount per transaction)			
ATT	0.015***	0.027***	0.037***	0.028***
	(0.005)	(0.002)	(0.002)	(0.002)
Observations	21,616	101,086	85,580	122,462

Notes: This table shows the average contact card-sales response to the adoption of contactless payments by merchant age. For each merchant age in columns (1)-(4), on the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT. The dependent variable is the log of contact card-sales amount, sales count, or amount per transaction. All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

5 Conclusion

In recent years, cashless payments have become a strong alternative to cash and their use is becoming increasingly popular around the world. Our paper provides support for this thesis by investigating the impact of the acceptance of a new cashless payment instruments, namely contactless cards, on merchants card sales by using a novel and unique card transactions data of 275,580 French merchants in 2018.

Using score matching and difference-in-difference techniques, we first find that the acceptance of contactless payments by merchants significantly increase their average annual card-sales amount and count compared to those who do not (by 15.5 percent for sales amount and by 17.1 percent for sales count). Therefore, accepting contactless payments contributes to an increase in total card-sales amount and count, either by attracting more consumers or by displacing non-card payments, or both. We also find evidence that the acceptance of contactless cards has a positive spillover effect on contact card payments of about 1.3 percent on average, but a negative one in the upper parts of the contact card-sales amount distribution (75th and 90th percentiles).

As contactless payments are intended to speed up small-value transactions at a point-of-sale in fast-paced environments where customers have few cashier alternatives most of the time, we analyze the impact of contactless technology adoption by business size and business sectors. We find evidence that the card-sales response of contactless payments acceptance are larger for small merchants (<EUR 25000) and businesses that make small amounts per transaction such as bakeries. However, accepting contactless cards has contrasted impacts on contact card sales in some sectors. While we observe a positive spillover on contact card sales in sectors such as leisure, we find support of a cannibalization between contactless and contact card sales in the sector of taxis.

Finally, we investigate the impact of the contactless technology adoption of new entrepreneurs who started their businesses in 2016. We observe that these new companies increase their annual card sales by 27.1 percent compared to those who had not yet accepted contactless payments, and benefit from a much stronger and positive spillover effect on contact card sales. More generally, the positive effect of contactless payment acceptance on card activity is found to decrease with the age of commerce.

This research can be extended in two directions. The first is related to the acceptance of contactless payments by mobile phones. To date, the number of mobile contactless payments is limited and does not allow for an in-depth analysis. However, this technology is increasingly popular with the younger generations and could replace card technologies. The second is precisely related to the substitution between contactless payment technologies, card or mobile, and paper-based payment instruments such as cash and cheques. The current set of data is limited to study whether the contactless payment technology is a substitute for cash payments for instance, and/or whether it can attract new customers who have a high preference for the contactless payment technology.

References

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267.

Agarwal, S., Amromin, G., Chomsisengphet, S., Landvoigt, T., Piskorski, T., Seru, A., and Yao, V. (2015). Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinancing program. Working Paper 21512, National Bureau of Economic Research.

Agarwal, S. and Qian, W. (2014). Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore. *American Economic Review*, 104(12):4205–30.

Agarwal, S., Qian, W., Yeung, B. Y., and Zou, X. (2019). Mobile Wallet and Entrepreneurial Growth. *AEA Papers and Proceedings*, 109:48–53.

Arango, C., Huynh, K. P., and Sabetti, L. (2015). Consumer payment choice: Merchant card acceptance versus pricing incentives. *Journal of Banking & Finance*, 55(C):130–141.

Athey, S. and Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, 74(2):431–497.

Autor, D. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21(1):1–42.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-In-Differences Estimates?*. *The Quarterly Journal of Economics*, 119(1):249–275.

Bose, N. and Das, S. (2017). Women's inheritance rights, household allocation, and gender bias. *American Economic Review*, 107(5):150–53.

Bounie, D., François, A., and Hove, L. V. (2017). Consumer Payment Preferences, Network Externalities, and Merchant Card Acceptance: An Empirical Investigation. *Review of Industrial Organization*, 51(3):257–290.

Bounie, D., François, A., and Waelbroeck, P. (2016). Debit Card and Demand for Cash. *Journal of Banking & Finance*, 73:55–66.

C. Srivastava, S., Chandra, S., and Theng, Y.-L. (2010). Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis. *Communications of the Association for Information Systems*, 27.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Callaway, B., Li, T., and Oka, T. (2018). Quantile treatment effects in difference in differences models under dependence restrictions and with only two time periods. *Journal of Econometrics*, 206.

Caselli, F. and Coleman, W. J. (2001). Cross-country technology diffusion: The case of computers. *American Economic Review*, 91(2):328–335.

CB (2018). CB en chiffres. https://www.cartes-bancaires.com/a-propos/cb-en-chiffres/.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs*. *The Quarterly Journal of Economics*.

Ching, A. T. and Hayashi, F. (2010). Payment card rewards programs and consumer payment choice. *Journal of Banking & Finance*, 34(8):1773–1787.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: making the theories face the facts. *Journal of Monetary Economics*, 51(1):39–83.

Crowe, M. and Tavilla, E. (2019). Tap to Pay: Will Contactless Cards Pave the Way for NFC Mobile Payments in the U.S.? . Staff discussion paper, Federal Reserve Bank of Boston.

Dague, L., DeLeire, T., and Leininger, L. (2017). The effect of public insurance coverage for childless adults on labor supply. *American Economic Journal: Economic Policy*, 9(2):124–54.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13:319–340.

Dehejia, R. H. and Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84(1):151–161.

Di Blasi, Z., Harkness, E., Ernst, E., Georgiou, A., and Kleijnen, J. (2001). Influence of context effects on health outcomes: A systematic review. *The Lancet*, 357(9258):757–762.

Egger, R. (2013). The impact of near field communication on tourism. *Journal of Hospitality and Tourism Technology*, 4.

Esselink, H. and Hernandez, L. (2017). The Use of Cash by Households in the Euro Area. ECB Occasional Paper 201, European Central Bank.

European Central Bank (2018). Payments statistics: 2017. https://www.ecb.europa.eu/press/pr/stats/paysec/html/ecb.pis2017.en.html. Press release, 14 September 2018.

Fan and Yu (2012). Partial identification of distributional and quantile treatment effect in difference-in-differences models. *Economics Letters*, 115:511–515.

Firpo, S. (2007). Efficient semiparametric estimation of quantile treatment effects. *Econometrica*, 75(1):259–276.

Fung, B., Huynh, K., and Sabetti, L. (2012). The Impact of Retail Payment Innovations on Cash Usage. Staff Working Papers 12-14, Bank of Canada.

Gaynor, M., Moreno-Serra, R., and Propper, C. (2013). Death by market power: Reform, competition, and patient outcomes in the national health service. *American Economic Journal: Economic Policy*, 5(4):134–66.

Gerhardt Schierz, P., Schilke, O., and W. Wirtz, B. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications*, 9:209–216.

Givord, P. (2014). Méthodes économétriques pour l'évaluation de politiques publiques.

Greenstone, M. and Hanna, R. (2014). Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72.

Hall, B. H. and Khan, B. (2003). Adoption of New Technology. NBER Working Papers 9730, National Bureau of Economic Research, Inc.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in southern california. *American Economic Review*, 94(1):317–328.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64(4):605–654.

Henry, C., Huynh, K., and Welte, A. (2018). 2017 Methods-of-Payment Survey Report. Staff Discussion Paper 2018-17, Bank of Canada.

Jonker, N. (2011). Card acceptance and surcharging: the role of costs and competition. *Review of Network Economics*, 10(2):1446–9022.

Koenker, R. W. and Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1):33–50.

Lamarche, C. (2010). Robust penalized quantile regression estimation for panel data. *Journal of Econometrics*, 157(2):396–408.

Raynor, W. J. (1983). Caliper pair-matching on a continuous variable in case-control studies. *Communications in Statistics - Theory and Methods*, 12(13):1499–1509.

Rogers, E. M. (2003). Diffusion of innovations, 5th edition. *Free Press, New York, NY*, page 551.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Schmeiser, M., Stoddard, C., and Urban, C. (2016). Student loan information provision and academic choices. *American Economic Review*, 106(5):324–28.

Smith, J. and Todd, P. (2005). Does matching overcome lalonde's critique of non-experimental estimators? *Journal of Econometrics*, 125(1-2):305–353.

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

Trütsch, T. (2014). The impact of contactless payment on spending. *International Journal of Economic Sciences*, 3(4):70–98.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27:425–478.

Wang, Z. and Wolman, A. (2016). Payment choice and currency use: Insights from two billion retail transactions. *Journal of Monetary Economics*, 84(C):94–115.

Zhang, Y., Zhang, G., Liu, L., Renzis, T. D., and Schmiedel, H. (2019). Retail payments and the real economy. *Journal of Financial Stability*, 44:100690.

Zimmerman, S. D. (2019). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review*, 109(1):1–47.

6 Appendix: Robustness Tests, Spillover Effect, Average and Quantile Contact Card-Sales Response (ATT and QTT)

In this section, we perform additional tests to study the robustness of our main results illustrated in Section 4. First, we use different types of matching methods, with or without replacement, to test the robustness of the matching. As our main analysis is carried out on the matched sample based on the radius matching (with replacement) with a 0.02 tolerance level, we specifically use the radius matching with a 0.01 tolerance level with and without replacement, and with a 0.02 tolerance level without replacement. We also investigate the robustness of our results using the matched sample based on the nearest neighbor score matching (Smith and Todd 2005 ; Abadie and Imbens 2006 ; Agarwal and Qian 2014). Table 8 displays the results and shows that regardless of the specification, they are quite robust, with very little variation in the estimated coefficients. Identical tests were also performed for the spillover effects; the results are reported in Table 11, and also confirm the stability of the initial results.

Table 8: Robustness Checks and Average Card-Sales Response (ATT)

	Caliper=0.01 with replacement (1)	Caliper=0.01 without replacement (2)	Caliper=0.02 with replacement (3)	Caliper=0.02 without replacement (4)	1-Nearest Neighbor with replacement (5)	1-Nearest Neighbor without replacement (6)	2-Nearest Neighbor with replacement (7)	2-Nearest Neighbors without replacement (8)
	Log(Sales amount)							
ATT	0.143***	0.144***	0.142***	0.143***	0.144***	0.143***	0.144***	0.146***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	Log(Sales count)							
ATT	0.159***	0.159***	0.158***	0.158***	0.159***	0.158***	0.159***	0.162***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	Log(Amount per transaction)							
ATT	-0.016***	-0.015***	-0.016***	-0.015***	-0.016***	-0.015***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	231,160	227,604	231,252	227,716	231,320	231,320	346,980	346,980

Notes: This table presents robustness checks of the ATT results in the matched sample shown in Table 2 using alternative specifications. In columns (1)-(4), we modify the matching algorithm by using radius matching with a 0.01 or 0.02 caliper with or without replacement. In columns (5)-(8), we use the nearest neighbor matching based on the estimated score. The dependent variable is the log of card-sales amount, sales count or amount per transaction. All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Second, we test the robustness of QTT estimations using the Callaway et al. (2018) strategy. The method considers identification and estimation of a particular distributional treatment effect parameter on the treated under a difference-in-difference setup when two periods are considered. It relies on the assumption that the dependence (the copula) between the change in the untreated potential outcomes and the initial level of untreated potential outcomes is the same for the treated and untreated merchants. To do so, we define 2015 to 2017 the treatment period. The results are displayed in Table 9 and also confirm the robustness of the main results. We also report in Table 12 the tests related to the spill over effects.

Table 9: Robustness Checks and Quantile Card-Sales Response (QTT)

		Log(Sales amount)	Log(Sales count)	Log(Amount per transaction)
		(1)	(2)	(3)
QTT	q=10	0.234***	0.211***	-0.021**
		(0.021)	(0.026)	(0.008)
	q=25	0.138***	0.137***	-0.018**
		(0.015)	(0.019)	(0.007)
	q=50	0.106***	0.114***	-0.013**
		(0.013)	(0.016)	(0.005)
	q=75	0.088***	0.119***	-0.012
		(0.016)	(0.018)	(0.008)
	q=90	0.066***	0.092***	-0.014
		(0.02)	(0.021)	(0.009)
Observations			462,504	

Notes: This table presents robustness checks of the QTT results in the matched sample shown in Table 2 using the Callaway et al. strategy. The dependent variable is the log of card-sales amount in column (1), the log of card-sales count in column (2) and the log of card amount per transaction in column (3). All regressions include group and time fixed effects. Robust bootstrapped standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Third, we study the robustness of our results by applying a Placebo test (Di Blasi et al., 2001 ; Autor, 2003 ; Givord 2014) using the same difference-in-difference procedure on our treatment and control groups but at a date with no significant activity. To do this, we suppose that 2015 and 2016 are good choices as these were periods when merchants had not yet adopted contactless payments. As expected, we do not find any significant impact (see Table 10).

Table 10: Placebo Test: Contactless Acceptance and Business Card sales

		Log(Sales amount)	Log(Sales count)	Log(Amount per transaction)
		(1)	(2)	(3)
ATT		-0.004	-0.005	0.001
		(0.003)	(0.003)	(0.001)
	q=10	-0.023	-0.026	-0.003
		(0.026)	(0.033)	(0.01)
	q=25	0.002	-0.008	0.001
		(0.018)	(0.022)	(0.008)
QTT	q=50	0.005	0.003	-0.003
		(0.017)	(0.02)	(0.006)
	q=75	0.004	0.007	0.003
		(0.019)	(0.022)	(0.01)
	q=90	-0.016	-0.016	0.008
		(0.025)	(0.026)	(0.011)
Observations			231,252	

Notes: This table presents robustness checks of the ATT and QTT results in the matched sample shown in Table 2 using the Placebo test. It reports the average (and quantile) card-sales response of merchants who are supposed to have accepted contactless payments in 2016 (while they really accepted it in 2018) compared to matched merchants who do not accept contactless payments. On the matched merchants, using linear regression, β_3 of equation (5) corresponds to the ATT, and to QTT when using quantile regression. The dependent variable is the log of card-sales amount in column (1), the log of card-sales count in column (2) or the log of card amount per transaction in column (3). All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level (for ATT) and bootstrapped standard errors (for QTT) are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Four, we report the robustness tests related to spillover effects. Table 11 presents robustness tests of the ATT results in the matched sample shown in Table 3 using alternative specifications. Table 12 reports robustness tests of the QTT results in the matched sample shown in Table 3 using Callaway et al. (2018) strategy. All the tests confirm the stability of the results obtained in the initial regressions.

Table 11: Robustness Tests, Spillover Effect and Average Contact Card-Sales Response (ATT)

	Caliper=0.01 with replacement (1)	Caliper=0.01 without replacement (2)	Caliper=0.02 with replacement (3)	Caliper=0.02 without replacement (4)	1-Nearest Neighbor with replacement (5)	1-Nearest Neighbor without replacement (6)	2-Nearest Neighbor with replacement (7)	2-Nearest Neighbors without replacement (8)
	Log(Sales amount)							
ATT	0.015***	0.016***	0.013***	0.016***	0.015***	0.014***	0.017***	0.017***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	Log(Sales count)							
ATT	-0.015***	-0.014***	-0.016***	-0.013***	-0.015***	-0.017***	-0.013***	-0.013***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	Log(Amount per transaction)							
ATT	0.03***	0.03***	0.029***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	231,160	227,604	231,252	227,716	231,320	231,320	346,980	346,980

Notes: This table presents robustness tests of the ATT results in the matched sample shown in Table 3 using alternative specifications. In columns (1)-(4), we modify the matching algorithm by using radius matching with a 0.01 or 0.02 caliper with or without replacement. In columns (5)-(8), we use the nearest neighbor matching based on the estimated score. The dependent variable is the log of contact card-sales amount, sales count or amount per transaction. All regressions include group and time fixed effects. Robust standard errors clustered at the merchant level are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 12: Robustness Tests, Spillover Effect and Quantile Contact Card-Sales Response (QTT)

		Log(Sales amount)	Log(Sales count)	Log(Amount per transaction)
		(1)	(2)	(3)
QTT	q=10	0.083***	0.079***	0.039***
		(0.021)	(0.026)	(0.008)
	q=25	0.023	0.019	0.053***
		(0.015)	(0.019)	(0.007)
	q=50	-0.013	-0.051***	0.043***
		(0.013)	(0.016)	(0.005)
	q=75	-0.037**	-0.103***	0.014*
		(0.016)	(0.018)	(0.008)
	q=90	-0.055***	-0.125***	-0.003
		(0.02)	(0.021)	(0.009)
Observations			462,504	

Notes: This table presents robustness tests of the QTT results in the matched sample shown in Table 3 using Callaway et al strategy. The dependent variable is the log of card-sales amount in column (1), the log of contact card-sales count in column (2) or the log of card amount per transaction in column (3). All regressions include group and time fixed effects. Robust bootstrapped standard errors are reported in parentheses. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.