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THE IMPACT OF CONTACTLESS PAYMENT ON SPENDING

Abstract:

This paper estimates the effect of contactless payment on the spending ratio in terms of transactions for different transaction types at the point-of-sale. The specifc devices that are investigated are debit and credit cards, to which the feature is embedded. Data is drawn from a national representative survey on consumer payment behavior in the US in 2010. Using propensity score matching to control for selection, the estimation shows that the contactless feature yields to a signifcant increase in the spending ratio at the point-of-sale for both payment methods. The average treatment effect on the treated for credit and debit cards is roughly 8 and 10 percent, respectively. These fndings indicate that the private industry can highly benefit from the innovation with respect to new revenue streams. This paper contributes to the existing literature in payment economics by analyzing one of the most recent payment products.

Keywords:

contactless payment, payment innovation, spending habits, credit and debit cards,
near-feld communication (NFC), propensity score matching

JEL Classification: C21, D12, D14

1 Introduction

The way consumers make daily payments has changed significantly in recent years due to innovations such as debit, credit and prepaid cards, online banking and mobile payments among others. By 2010, consumers in the US have undertaken within a month on average 50 percent of their transactions by payment cards, 40 percent by paper instruments such as cash and 9.2 percent by electronic and other instruments (Foster et al., 2013). Meanwhile, new forms of retail payment innovations have come up among which contactless payment.[1]

This paper investigates the impact of contactless payment on individual spending in terms of transactions for different transaction types at the point-of-sale (POS). This new form of payment device has mainly been developed by the private industry sector for revenue purposes. The specific technology is embedded in the most prominent payment cards and mobile phones. Its convenience, safety and efficiency, which is expected to be perceived as superior to cash, should support the proliferation of electronic payments and substitution away from cash, which still accounts for a significant share of transactions.

Understanding the effect of contactless payment on individual spending habits is crucial for three main reasons. First and foremost, there is limited knowledge on the adoption and usage behavior of the contactless payment innovation due to its very recent emergence and establishment. Retailers can use the information for evaluating whether to invest in the most up-to-date payment terminals in order to have full gains of the newest payment technologies because an efficient payment process is one of the most crucial conditions to reduce waiting lines at the counter and consequently a decline in sales inferring from negative shopping experiences.

Second, the findings provide information on specific usage and adoption patterns among cashless payment means, which may be relevant for financial intermediaries with respect to managerial, promotional and revenue purposes. In general, increasing card transactions that they might process will result in rising revenue streams generated through their fees.

Third, the paper provides information for policy makers with regards to evaluating and implementing interchange fee regulation for payment cards, which is an ongoing issue in several countries (cf. Weiner and Wright, 2005) such as the US (Johnson, 2014), Switzerland (Brouzos, 2014) and the European Union (European Parliament, 2014).[2] For instance, more card transactions imply higher costs on shop owners due to the current interchange fee structure, as it is demon-strated in Wakamori and Welte (2012). Additionally, Wiechert (2009) concludes for Swiss retailers that contactless payment increases the payment costs for retail shops even more dramatically since it

[1] Contactless payment is based on the near-field communication (NFC) technology, which is a standard radio communication technology that allows to connect devices within 4 cm range by waving or tapping the objects without providing a signature or PIN for verification. The feature is usually embedded in conventional payment cards, but also in other devices such as mobile phones and key fobs. For instance, contactless credit cards allow making instantaneous payment transactions by just waving the card over the card reader. The terms 'NFC' and 'contactless' are used interchangeably in this study.

[2] I refer to Rochet and Wright, 2010; Evans and Schmalensee, 2005; Rochet and Tirole, 2002 and Rochet, 2003 among others for a theoretical consideration of the interchange fee regulation and to Jaeger et al. (2011) with special focus on Switzerland.

would mean the transfer of low-cost cash payments to cards implying a higher burden on interchange fees. The cost increase is more accentuated for micro than macro payments.[3] However, the provision of an efficient and cheap payment service is crucial to underpin the sound operation of the economy. This is also highlighted in the new strategic focus for financial services announced by the president of the Federal Reserve Bank of Cleveland (Pianalto, 2012), which specifically considers payment preferences of end consumers when making future decision about the payment system. Providing such information in this paper contributes to support the decision-making process.

This paper can be seen as complementary to the strands of literature in payment economics and makes a contribution in the context of financial innovation (e.g. Alvarez and Lippi, 2009; Amromin and Chakravorti, 2007; Drehmann et al., 2004; Humphrey et al., 2001; von Kalckreuth et al., 2009; Schuh and Stavins, 2010) and may be relevant for the literature in the two-sided markets as well (e.g. Rysman, 2007; Rochet and Tirole, 2002; Rochet and Wright, 2010). Although the model in this paper does not account for price sensitivity and the two-sidedness in terms of merchant decisions, the study gives insights in the individual adoption and usage of contactless payment cards under the interchange fee regulation in 2010 from a consumer's point of view.[4]

The topic is also relevant in the context of efficient payment methods. Checkout time is an important determinant for the choice of payment means. This is highlighted in Klee (2006) who finds evidence that debit cards are preferred over checks to save time. Contactless payment allows to pay efficiently and may therefore lead to higher transaction frequency. Borzekowski and Kiser (2008) quantify the effect of contactless debit cards in the US applying rank-order-logit models and prospect an increase in market share of contactless debit cards compared to cash, check and credit cards because merchants can save up to 0.03 USD per transaction by accepting contactless debit cards, which is exclusively driven by faster checkout.[5]

There is substantial literature on the relationship between reward programs, interest free periods and use of credit cards, which this paper is related to since time savings at the checkout are associated with pecuniary incentives. Participation in loyalty programs and access to interest free periods tend to increase credit card use at the expense of alternative payment methods such as debit cards and cash (Simon et al., 2009; Agarwal et al., 2010; Ching and Hayashi, 2010; Carbó-Valverde and Linares-Zegarra, 2009; Arango et al., 2011). There are also some consumer-side studies conducted by the private industry sector. For example, Mastercard (2013) observes an increased usage of Mastercard-PayPass payment cards both in terms of value spending and transaction frequency.[6] This research, however, tend to be biased because it might serve as a sales argument for merchants and the data is restricted to

[3] Avoiding the cost increase for retailers entails growth in sales or reduction in operation costs. If both are not sufficient, an overall card fees reduction or a discount for micro payment transactions is more appropriate (Wiechert, 2009).
[4] In July 2010, the Dodd-Frank Wall Street Reform was enacted capping interchange fees of debit cards at 0.12 USD per transaction compared to 0.44 USD before the reform (Board of Governors of the Federal Reserve System, 2011). The interchange fee of credit cards was roughly around 3 percent of the transaction amount in 2010 (Visa USA, 2010).
[5] With average costs of 0.70 USD per debit card transaction.
[6] The Mastercard-PayPass payment card is NFC-enabled.

Mastercard customers only. This paper aims to provide more objective research to gain insights in individual payment habits in the context of retail payment innovations.

The novelty of this study is twofold. On the one hand, due to the very recent emergence of contactless payment, it exists only limited knowledge of its effect on individual payment habits. This paper fills the gap in this relatively new field. On the other hand, using unique, detailed and representative individual survey data from the US dated 2010 allows to investigate the causal effect of contactless payment on spending of the most prominent payment cards (credit and debit cards) for different transaction types (POS payments distinguished by retail and services payments) by applying propensity score matching to control for selection bias, which is inherent in this setting. Since the data set encompasses the rating of perceived characteristics such as ease of use, security, speed, setup costs of numerous payment instruments, I also can control for unobserved heterogeneity (cf. Jonker, 2007; Kim et al., 2006; Ching and Hayashi, 2010).

My empirical analysis yields the following important results. Using the 2010 Survey of Consumer Payment Choice (SCPC) I estimate the impact of contactless payment on the spending ratio at the individual level. First, I find that the average treatment effect on the treated of contactless credit cards leads to an increase in the spending ratio of 8.3 percent at the POS while the effect for retail and services purchases is 4.8 and 3.5 percent, respectively. Second, the average treatment effect on the treated of contactless debit cards exerts a positive effect on the spending ratio of 10 percent at the POS. In terms of retail and services payments the impact results in 4.5 percent. Sensitivity analysis shows that the results are robust to unobserved heterogeneity.

The structure of the paper is as follows. Section 2 derives the theoretical framework and section 3 describes the data. In section 4, I elaborate my estimation strategy and present the econometric model. Section 5 includes the results of the empirical analysis and section 6 concludes.

2 Theoretical Considerations

The theoretical background for this study is drawn from technology acceptance models, which aim at explaining the adoption and usage conditions of innovations. There are numerous models that explain technology adoption and use from different points of view, from which I choose the most tailored to the research question.

Technology Acceptance Model (TAM). This model explains when individuals will accept and make use of a technology and has originally been applied to predict end-user acceptance of information systems within organizations. The model consists of two main technology acceptance measures: Perceived Usefulness and Perceived Ease of Use. Davis (1989, p. 320) defines the former as “the degree to which a person believes that using a particular system would enhance his or her job performance”. Enhanced efficiency, time savings and convenience are subjects to Perceived Usefulness, which are pertaining to contactless payment (Wang, 2008), and therefore should foster its deployment. Perceived Ease of Use is specified as “the degree to which a person believes that using a particular system would be free from effort” (Davis, 1989, p. 320). Accordingly, contactless payment is more likely to be used if it is easy to handle.

Innovation Diffusion Theory (IDT). The theory, developed by Rogers (2003), explains how and why innovations spread through societies. It basically consists of two interrelated processes, namely the diffusion and adoption process. The former can be described as a macro process that explains how innovations spread through societies whereas the latter is a micro process focusing on the individual's decision making process of adopting innovations.

The innovation-decision process consists of five consecutive stages: (1) Knowledge, (2) Persuasion, (3) Decision, (4) Implementation, and (5) Confirmation (Rogers, 2003). In the Knowledge stage, the individual learns about the emergence of an innovation influenced by prior conditions (previous practice, problems and needs, innovativeness, and norms of the social system) and by his own characteristics (socioeconomic characteristics, personality variables and communication behavior). Thus, some adoption mechanisms are predetermined. Subsequently, opinions are formed about the innovation in the Persuasion stage where six innovation characteristics affect the adoption of innovations: relative advantage, complexity, compatibility, trialability, and observability (Rogers, 2003). The first three concepts are similar to the ones in the previous TAM-model.

Of these constructs, the first three of them have provided the most accurate prediction for the intention to use NFC-enabled mobile credit cards (Leong et al., 2013). With respect to complexity, (mobile) contactless payment is expected to increase the convenience of payments and therefore usage by reducing the need for coins and cash in small transactions (Mallat et al., 2004). In the third stage, the Decision stage, the individual finally chooses to adopt or reject the innovation based on the former stages.

Unified Theory of Acceptance and Use of Technology (UTAUT). This model represents an extension of the previous TAM and IDT model (among others) and explains user intentions and subsequent usage behavior (Venkatesh et al., 2003). The model consists of four key effects and four moderating factors. While the first three core constructs Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) directly influence the behavioral intention, the forth construct Facilitating Conditions (FC) have a direct impact on use behavior. The four remaining factors Gender, Age, Experience, and Voluntariness of Use thereby moderate the initial key effects.

Empirical testing has shown that PE, which is similar to Perceived Usefulness in the IDT model, is the strongest predictor of intention in the context of the UTAUT. Time savings, usefulness and convenience are concepts which measure performance expectancy and are positively related to contactless payment (Yu, 2012). These characteristics should therefore advance the usage of contactless payment. Gender studies have revealed that PE is especially salient for men since they tend to be more task-oriented. Also, age differences determine technology adoption (Venkatesh et al., 2003).

EE is evaluated by questions about the difficulty of learning, interacting and becoming skillful in applying new technologies (Yu, 2012). Venkatesh et al. (2003) show that this construct is only significant for users with a non-existing or low experience level, becoming non-significant over periods of extended and sustained usage. EE is more salient for women than for men whereas increasing age is associated with difficulties in processing complex stimuli (Venkatesh et al., 2003). This implies younger cohorts to be more prone to contactless payment.

SI suggests that individuals' behavior is affected by the way in which they believe others will view them as a result of having used the technology (Venkatesh et al., 2003). Its role in technology acceptance decisions is complex and influences individuals through three mechanisms: compliance, internalization and identification. The latter two intend to alter an individual's belief structure and/or to cause an individual to respond to potential social status gains. The former mechanism causes an individual to alter his intention in response to social pressure. Positively attributed characteristics of contactless payment such as transaction speed and convenience positively alters the individual's belief structure and hence can positively influence usage. However, the reliance on others' opinions, i.e. manifested itself in social pressure, is particularly significant in the early stages of the technology experience when individuals are uninformed. This in turn will attenuate over time since a more instrumental (rather than social) basis will affect the technology usage due to increased experience (Venkatesh et al., 2003). Social Influence is more salient for women regarding the technology acceptance decision process since they tend to be more sensitive to others' opinions. Moreover, elderly people are more likely to place increased salience on social influences since they possess higher affiliation needs (Venkatesh et al., 2003).

In sum, the adoption and usage of contactless payment is influenced by various factors that are partly predetermined and therefore it follows a non-random pattern.

3 Data

3.1 Source

Data is drawn from the Federal Reserve Bank of Boston that supports the Consumer Payments Research Center (CPRC), which regularly conducts the Survey of Consumer Payment Choice (SCPC).[7] It is a rich nationally-representative and publicly-available data set on consumer payment behavior in the US. The survey focuses on the adoption and use of nine common payment instruments including cash.[8] Also, the perceptions on method of payment attributes are questioned and information on demographics is provided. The latest publicly-accessible data dates back to 2010 and was administrated online by the RAND Corporation, using RAND's American Life Panel, to a random sample of 2102 US consumers primarily in October during fall 2010 whose responses were weighted to represent all US consumers ages 18 years and older. The reporting unit of the SCPC is an individual consumer in the US. The reason to monitor individuals rather than households stems from the fact that it is unlikely that the head of the household can track the payment behavior of all household members in detail. However, some information about each reporting consumer's household is collected in the survey such as income. It is worth noting that the estimates are not adjusted for seasonal variation, inflation or item non-response (missing values). Also, the tumultuous years after the financial crisis in 2008

[7] See Foster et al. (2013) for a comprehensive description of the data.
[8] These include check, bank account number payment, online banking bill payment, money order, traveler's check, debit, credit and stored-value cards.

accompanied by a severe recession could have led to unusual reporting of the number of payments.

3.2 Description

The survey specifically asks respondents if one of their credit and debit cards was equipped with the contactless feature, but unfortunately does not provide exact information on the usage of the technology. Instead, detailed statistics on the usage of conventional credit and debit cards are available as well as their adoption rates. Table 1 shows the market shares of contactless and conventional credit and debit cards as well as the corresponding use of the latter. It reveals that about 9 percent (187 individuals) of the entire sample of 2084 respondents reported that their credit card is equipped with the contactless feature, whereas approximately 12 percent (258 individuals) have stated to possess a contactless debit card. In contrast, more than 70 percent have a conventional credit card and around 78 percent a debit card. Credit and debit cards are used at least once within a month by 56 and 63 percent of people in the sample.

Table 1: Adoption and Usage of Payment Cards

Variable	Mean	Std. Dev.	N
Contactless Credit	0.092	0.289	2084
Contactless Debit	0.124	0.329	2084
Credit	0.703	0.457	2088
Debit	0.784	0.411	2090
Credit Usage	0.568	0.495	2059
Debit Usage	0.631	0.483	2056

Note: Usage describes the fact that respondents make the corresponding type of payment at least once in a typical month. Survey weights used.

To estimate the impact on spending, I refer to the exact number of specific card transactions (credit and debit cards) that an individual has conducted within a typical month distinguished by types of payment at the POS, i.e. retail goods[9] and services.[10] Accuracy of reporting was ameliorated by asking respondents the number of payments for a typical period rather than a specific calendar period. Typical periods shall represent an implicit average of their perceived regular or trend behavior and have the advantage of eliminating unusual events that might affect high-frequency payments and veil longer-run trends. Also, respondents are allowed to choose the frequency (week, month or year) that best suits their recollection of payments for each type of transaction (Foster et al., 2013). On the basis of the responses, the number of payments was calculated for a typical month corrected for invalid data entries. Table 2 and 3 provide summary statistics on the number of transactions of different payment types per month distinguished by contactless card adopters. Additionally, a simple

[9] These include items purchased in food and grocery stores, superstores, warehouses, club stores, drug or convenience stores, gas stations, department stores, electronics, hardware and appliances stores.
[10] These include services paid for restaurants, bars, fast food and beverage, transportation and tolls, medical, dental, and fitness, education and child care, personal care (e.g. hair), recreation, entertainment and travel, maintenance and repairs, other professional services (business, legal etc.) and charitable donations.

mean comparison test (t-test) between non-innovators and innovators is reported showing (significant) differences in the average spending.

As shown in Table 2, contactless credit card adopters undertake around 9 credit card payments more at the POS within a month than non-adopters (17 vs. 8 transactions) with approximately 5 and 4 transactions more for retail goods and services, respectively (10 vs. 5 and 7 vs. 3 payments). These means are significantly different from each other indicating enhancement in payment frequency for innovators. This holds also for overall payment card statistics at the POS. Innovators pay on average per month 31 times by payment cards at the POS (18 retail and 13 services payments), while non-innovators conduct around 23 payments (14 retail and 19 services payments). These mean differences are highly significant. On the contrary, contactless credit card adopters pay significantly less frequently by cash for services (roughly 2 payments) than non-innovators.

Table 2: Number of Payment Types by Contactless Credit Card Adopters per Month

	Non-Innovator				Innovator				t-Test
Variable	Mean	Std. Dev.	Max.	N	Mean	Std. Dev.	Max.	N	Mean Diff
CC POS	8.36	16.61	117.4	1869	17.1	25.44	108.71	188	−8.67***
CC Retail	4.99	10.72	100	1851	9.81	14.83	65.22	188	−4.67***
CC Services	3.45	7.61	95.66	1849	7.39	12.34	86.96	186	−3.99***
DC POS	15.09	23.03	139.14	1868	14.52	24.14	130.45	185	0.67
DC Retail	9.22	15.13	108.71	1857	8.59	15.37	86.97	184	0.67
DC Services	6.06	10.49	100	1834	5.95	10.58	43.48	185	0.00
SVC POS	0.39	1.81	20	1849	0.21	1.1	12	183	0.18
SVC Retail	0.24	1.26	20	1843	0.15	0.87	10	182	0.08
SVC Services	0.15	0.77	8.69	1839	0.06	0.31	2	181	0.09*
Overall Card POS	23.61	26.72	165.22	1886	30.77	35.48	173.93	190	−7.82**
Overall Card Retail	14.21	17.57	109.71	1884	17.9	21.27	108.71	190	−3.92*
Overall Card Services	9.41	12.4	105	1884	13.01	16.91	86.96	189	−3.90**
Cash POS	16.56	19.26	130.45	1881	14.05	17.87	108.71	187	3.01
Cash Retail	9.52	12.72	100	1822	8.38	11.65	65.22	185	1.07
Cash Services	7.27	9.91	86.96	1813	5.75	8.66	43.48	185	1.95**
Total POS	42.84	38.24	245.5	1893	47.05	42.87	217.41	191	−4.62
Total Retail	24.91	24.19	153.19	1893	27.25	26.31	148.84	191	−2.75
Total Services	17.93	19.32	158	1893	19.8	20.41	91.73	191	−1.87

Note: Survey weights used. Subcategories do not sum to main category due to rounding and weighting. For brevity, the minimum is dropped but equals zero for every type of payment. T-test of mean differences of innovator and non-innovator. They can differ from true values due to rounding and weighting. Significance levels 1% ***, 5% ** and 10% *. CC represents credit cards, DC debit cards and SVC stored-value cards. Overall card payments are the sum of CC, DC and SVC payments. Total POS payments are the sum of overall card POS payments, cash POS payments plus check and money order payments.

Table 3 distinguishes the number of transactions by contactless debit card adopters and non-adopters. Mean comparison tests between adopters and non-adopters reveal that statistically significant differences in the transaction frequency exist. Innovators buy goods and services at the POS by debit cards more frequently than non-innovators, namely 4 and 6 transactions more within a month (13 vs. 9 and 11 vs. 5 payments, respectively). Also, their overall card and total POS payments for services exceed those of non-adopters by 4 and 6 transactions, respectively. In contrast, they transact 5 payments fewer by credit cards at the POS (4 vs. 10 transactions) than non-innovators.

Table 3: Number of Payment Types by Contactless Debit Card Adopters per Month

	Non-Innovator				Innovator				t-Test
Variable	Mean	Std. Dev.	Max.	N	Mean	Std. Dev.	Max.	N	Mean Diff
CC POS	9.83	18	117.4	1875	4.37	15.26	108.71	181	5.56***
CC Retail	5.88	11.5	100	1858	2.35	8.59	65.22	180	3.51***
CC Services	4.06	8.34	95.66	1854	2.03	7.18	43.48	180	2.06***
DC POS	13.76	22.53	139.14	1876	24.13	25.13	130.45	179	−10.33***
DC Retail	8.64	15.12	86.96	1865	12.85	14.8	108.71	178	−4.20***
DC Services	5.29	9.85	100	1843	11.33	13.02	65.22	178	−6.14***
SVC POS	0.3	1.51	17.39	1853	0.88	2.94	20	180	−0.48
SVC Retail	0.17	0.92	12	1848	0.66	2.37	20	178	−0.40
SVC Services	0.13	0.72	8.7	1843	0.22	0.85	4.35	178	−0.08
Overall Card POS	23.6	27.15	173.93	1893	29.04	31.02	173.93	183	−5.25
Overall Card Retail	14.4	17.98	108.71	1891	15.65	17.88	109.71	183	−1.08
Overall Card Services	9.23	12.38	105	1890	13.39	15.75	86.96	183	−4.16**
Cash POS	15.96	18.92	130.45	1850	18.98	20.54	108.71	179	−3.11
Cash Retail	9.3	12.63	100	1831	10.22	12.57	65.22	177	−0.91
Cash Services	6.88	9.64	86.96	1821	8.89	10.78	43.48	178	−2.20
Total POS	42.24	37.96	245.5	1900	50.34	42.95	196.84	184	−8.17
Total Retail	24.88	24.43	153.19	1900	26.91	24.14	148.84	184	−1.93
Total Services	17.36	18.82	158	1900	23.43	22.61	117.4	184	−6.24**

Note: Survey weights used. Subcategories do not sum to main category due to rounding and weighting. For brevity, the minimum is dropped but equals zero for every type of payment. T-test of mean differences of innovator and non-innovator. They can differ from true values due to rounding and weighting. Significance levels 1% ***, 5% ** and 10% *. CC represents credit cards, DC debit cards and SVC stored-value cards. Overall card payments are the sum of CC, DC and SVC payments. Total POS payments are the sum of overall card POS payments, cash POS payments plus check and money order payments.

In sum, contactless credit and debit card adopters undertake statistically significantly more transactions by their corresponding payment cards compared to non-adopters while this also holds for overall card services payments.

For the purpose of the analysis, I compute the ratio of credit and debit card transactions separately to total payments at the POS, which is a more robust measurement towards outliers.[11] The majority of individuals exhibit a very small spending ratio both for credit and debit cards (see Figures 1 and 2) because roughly 31 percent and 35 percent of individuals have stated to had conducted zero credit and debit card payments per month, respectively (only restricted to those who possess a

[11] The total number of POS payments encompasses cash, check, money order, debit, credit and stored-value card payments.

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credit and debit card). This may stem either from those who did not make any purchases during a typical month or from those who forgot or refused to report any payments. Thus, the reasons for reporting zero payments may differ from the determinants of the actual non-negative integer number of card payments recorded.

Figure 1: Share of Credit Card Payments per Month at the POS

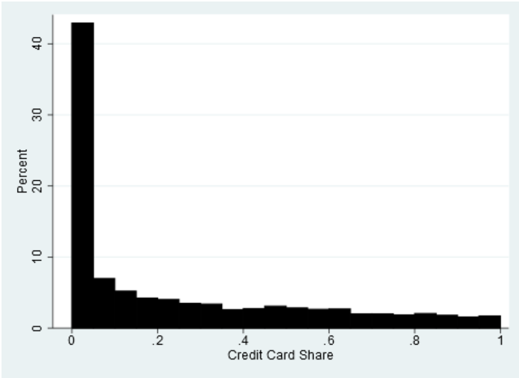
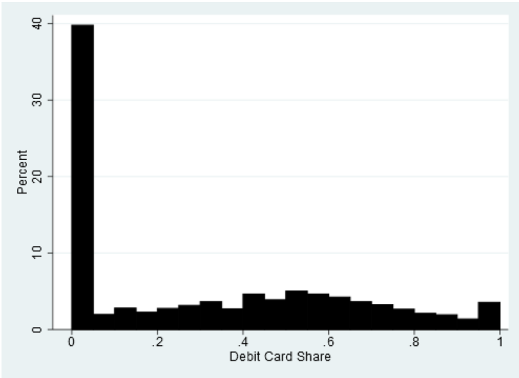


Figure 2: Share of Debit Card Payments per Month at the POS



The data set also provides rich information about consumer demographic characteristics and financial status. Tables 4 and 5 give insights in demographic characteristics and financial status of contactless credit and debit card holders separately. Obviously, referring to Table 4, the sample of contactless credit card adopters is more skewed towards higher income and education brackets as well as higher asset shares. For instance, 14 and 25 percent of individuals earning 125000 USD above and have completed some post graduate studies possess a contactless credit card. On average, innovators also withdraw money less frequently than non-innovators and are mostly male, working and married compared to non-innovators.

Table 4: Sample Summary Statistics of Credit Card Adopters

	Non-Innovator					Innovator				
Variable	Mean	Std. Dev.	Min.	Max.	N	Mean	Std. Dev.	Min.	Max.	N
Income (in 1000)										
<25	0.26	0.44	0	1	1890	0.13	0.34	0	1	190
25-49	0.28	0.45	0	1	1890	0.22	0.41	0	1	190
50-74	0.21	0.41	0	1	1890	0.26	0.44	0	1	190
75-99	0.11	0.32	0	1	1890	0.19	0.39	0	1	190
100-124	0.08	0.26	0	1	1890	0.07	0.25	0	1	190
>125	0.07	0.26	0	1	1890	0.14	0.35	0	1	190
Education										
<High School	0.05	0.22	0	1	1893	0.08	0.27	0	1	191
High School	0.4	0.49	0	1	1893	0.28	0.45	0	1	191
Some College	0.29	0.45	0	1	1893	0.23	0.42	0	1	191
College	0.15	0.36	0	1	1893	0.17	0.37	0	1	191
Post Graduate	0.11	0.32	0	1	1893	0.25	0.43	0	1	191
Employment										
Working	0.62	0.49	0	1	1893	0.7	0.46	0	1	191
Retired	0.19	0.39	0	1	1893	0.18	0.39	0	1	191
Unemployed	0.1	0.3	0	1	1893	0.06	0.24	0	1	191
Marital Status										
Single	0.2	0.4	0	1	1893	0.08	0.27	0	1	191
Married	0.62	0.49	0	1	1893	0.77	0.42	0	1	191
Others										
Male	0.48	0.5	0	1	1893	0.57	0.5	0	1	191
Age	46.6	16.82	18	109	1893	45.2	15.7	21	88	191
HH Members	1.4	1.56	0	9	1893	1.08	1.22	0	5	191
Assets	1.31	8.21	0	100	1807	1.54	8.19	0	78	183
Cash WD	6.15	12.31	0	434.8	1885	3.74	3.67	0	30.4	191

Note: Survey weights used. Subcategories do not sum to main category due to rounding and weighting. Cash withdrawals (WD) per month. Assets (in 1000) do not include houses.

Contrarily, the sample of contactless debit card adopters is more skewed towards the lower income and education brackets as well as lower wealth status, as high-lighted in Table 5. Approximately 32 percent of innovators earn less than 25000 USD and around 40 percent graduated from high school. Furthermore, they are mostly male, working, younger and single compared to non-innovators. Also, they withdraw cash around twice as much as non-innovators (10 vs. 5 withdrawals). This reflects higher preferences for out-of-the-way than credit payments, which cash and debit cards can provide. Contactless debit card holders seem not to adopt contactless payment for the purpose of reducing cash transactions, which could indicate complementarity of cash and debit cards.

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Table 5: Sample Summary Statistics of Debit Card Adopters

	Non-Innovator					Innovator				
Variable	Mean	Std. Dev.	Min.	Max.	N	Mean	Std. Dev.	Min.	Max.	N
Income (in 1000)										
<25	0.23	0.42	0	1	1895	0.32	0.47	0	1	184
25-49	0.27	0.44	0	1	1895	0.28	0.45	0	1	184
50-74	0.21	0.41	0	1	1895	0.23	0.42	0	1	184
75-99	0.13	0.33	0	1	1895	0.07	0.25	0	1	184
100-124	0.08	0.27	0	1	1895	0.04	0.2	0	1	184
>125	0.08	0.27	0	1	1895	0.06	0.23	0	1	184
Education										
<High School	0.05	0.21	0	1	1900	0.1	0.3	0	1	184
High School	0.38	0.48	0	1	1900	0.44	0.5	0	1	184
Some College	0.29	0.45	0	1	1900	0.28	0.45	0	1	184
College	0.16	0.36	0	1	1900	0.11	0.32	0	1	184
Post Graduate	0.13	0.34	0	1	1900	0.07	0.25	0	1	184
Employment										
Working	0.61	0.49	0	1	1900	0.73	0.45	0	1	184
Retired	0.2	0.4	0	1	1900	0.11	0.31	0	1	184
Unemployed	0.09	0.29	0	1	1900	0.11	0.31	0	1	184
Marital Status										
Single	0.18	0.38	0	1	1900	0.23	0.42	0	1	184
Married	0.64	0.48	0	1	1900	0.59	0.49	0	1	184
Others										
Male	0.47	0.5	0	1	1900	0.56	0.5	0	1	184
Age	47.2	16.87	18	109	1900	41.1	14.49	19	77	184
HH Members	1.31	1.5	0	9	1900	1.79	1.72	0	8	184
Assets	1.34	8.27	0	100	1818	1.28	7.76	0	80	172
Cash WD	5.35	9.98	0	434.82	1893	10.1	20.05	0	130.5	184

Note: Survey weights used. Subcategories do not sum to main category due to rounding and weighting. Cash withdrawals (WD) per month. Assets (in 1000) do not include houses.

Previous studies have found significant evidence that perceptions about payment attributes such as costs, safety and convenience improve the explanation of consumer payment decisions since they largely account for unobservable preferences (e.g. Jonker, 2007; Schuh and Stavins, 2011). The SCPC explicitly asks respondents to evaluate their perceptions about debit and credit cards in terms of security, setup, acceptance, cost, records and convenience on a categorical scale from one to five, where the latter implies the strongest view. Innovators in general rate the six characteristics listed as higher than non-innovators implying that contactless payment might have subtly and positively altered the perception and affinity towards these cards (see Table 6). It is noteworthy that especially convenience is highly attributed to contactless payment. Costs for debit cards are perceived as lower by innovators than non-innovators in contrast to credit cards, which costs are rated higher by contactless credit card adopters.

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Table 6: Statistics of Perceived Characteristics

	Credit Cards						Debit Cards					
	NI			I			NI			I		
Variable	Mean	Dev.	N	Mean	Dev.	N	Mean	Dev.	N	Mean	Dev.	N
Security	3.09	1.26	1886	3.29	1.27	191	3.04	1.18	1893	3.44	1.29	182
Setup	3.69	1.14	1889	3.95	0.95	191	3.97	0.93	1894	4.16	0.89	184
Acceptance	4.44	0.81	1889	4.5	0.69	190	4.32	0.82	1893	4.51	0.75	184
Cost	2.85	1.35	1886	2.93	1.36	190	3.96	0.98	1890	3.73	1.08	183
Records	4.3	0.85	1881	4.43	0.76	190	4.1	0.93	1888	4.36	0.68	184
Convenience	4.25	1.02	1884	4.49	0.79	191	4.27	0.97	1891	4.49	0.93	184

Note: Survey weights used. The perceived characteristics are measured with a Likert scale ranging from one to five representing five the strongest view. Dev. refers to standard deviation.

The perceived characteristics of credit and debit cards are constructed for the purpose of this paper as the average of each respondent's perception relative to all other payment methods at the POS similar to the procedure in Schuh and Stavins (2011) and Arango et al. (2011). It is calculated as

$$RCHAR_{kij} = \frac{CHAR_{kij}}{CHAR_{kij'}}$$

where k describes the six characteristics such as security, setup, acceptance, cost, records and convenience, i indexes the consumer, j relates to the payment instrument debit or credit card and j' is every other payment instrument besides j that is commonly used at the POS.[12] The construction is applied to every consumer regardless of the adoption stage of the payment methods. This allows normalizing the perception of a particular attribute by the individual's overall absolute perceived levels of satisfaction across payments at the POS (Arango et al., 2011).

To conclude, the descriptive statistics distinguished by innovators and non-innovators, defined by the adoption of contactless payment either for credit or debit cards, has offered some suggestive evidence that contactless payment leads to increased spending at the POS. Also, there is strong evidence that individuals do not randomly adopt the contactless payment innovation because some distinct adoption patterns between innovators and non-innovators are observable. Lastly, the perception of attributed characteristics towards credit and debit cards analyzed separately for innovators and non-innovators raises issues about endogeneity since positively attributed experiences of contactless payment may have affected its usage. The next section shall outline my empirical strategy to estimate the causal relationship of contactless payment on spending.

[12] Such as cash, stored-value cards and checks.

4 Methodology

4.1 Identifying Assumptions

To estimate the relationship between contactless payment and the spending ratio one can use standard OLS regression:

$$TRANSR_{ij} = \alpha I_{ij} + X_i + \varepsilon_i$$

where $TRANSR_{ij}$ is the share of transactions of individual i for payment method j, where j relates to debit or credit cards, relative to every other payment instrument j' besides j that is commonly used at the POS, I_{ij} takes the value of one if the individual is an innovator, i.e. a contactless payment adopter for payment method j, X_i are the observed characteristics for individual i and ε_i is the error term.[13] It is necessary that the variable I_{ij} is strictly exogenous to obtain an unbiased estimate of the causal parameter α. However, as the descriptives have shown, it is most likely that the adoption of the contactless feature (I_{ij}) is non-randomly assigned and thus the estimate may be biased and inconsistent (selection bias). There is great concern that some unobserved variables cause individuals to select into treatment and simultaneously to make more card payments. For instance, individuals could deliberately adopt contactless payment because they pay generally more by payment cards resulting in higher preferences towards the contactless technology. The utility of contactless payment might be much greater for these individuals than for others.

Moreover, it might be the case that I_{ij} is correlated with some other variables that also have an impact on the number of payments and cannot be measured directly (omitted variable bias). For instance, individuals that frequently use payment cards are specifically addressed by card issuers promoting the use of the contactless feature. Another important unobserved factor that might determine the adoption and usage of contactless payment could be an individual's affinity for new technologies, labeled personal innovativeness that influences preferences for electronic payments and the likelihood of adopting payment innovations.[14]

Further, it is most likely that contactless payment and spending suffer from reverse causality since contactless payment may induce individuals to make more transactions or individuals could adopt contactless payment to meet their personal preferences for frequent usage of payment cards. It is thus not evident if innovation drives spending or vice-versa.

[13] Other payment methods used at the POS are cash, stored-value cards, checks and money order.

[14] One might also consider the fact that the payment market is inherently characterized by a special market structure, i.e. the two-sided market, where network effects are predominant. To put it differently, the value of contactless payment for a consumer depends on the number of others using it. If the critical level of users had not been exceeded, the merchants would not invest in payment terminals and offer this payment method due to small economies of scale. This is typically referred to as the chicken-and-egg problem. Hence, the adoption and usage of contactless payment may face feedback effects, implying that consumers will actually choose contactless payment conditional on the number of terminals available that allow deploying this technology. However, this issue cannot be addressed adequately in the estimation due to data restrictions.

These biases all stem from endogeneity, i.e. the regressor I_{ij} is correlated with the error term ε_i. In these circumstances, OLS provides biased estimates of the effect of the treatment I_{ij}.[15] A common and reliable methodology to control for endogeneity is the instrumental variable (IV) research design providing high order of internal validity. In this sense, the IV (or alternatively the excluded instrument) must be highly correlated with the endogenous explanatory variable - the treatment I_{ij} - and must not be correlated with the error term ε_i. However, the IV estimates are only as good as the excluded instruments used. It has been cumbersome to find plausible instruments in this context.

A significant amount of unobserved heterogeneity can be captured by the inclusion of individuals' perceptions on payment cards characteristics (Jonker, 2007; Kim et al., 2006; Ching and Hayashi, 2010).[16] Also, some proxy variables that account for personal innovativeness help to control for unobservables. Therefore, the issue of endogeneous treatment is largely mitigated. However, the problem of non-random assignment into treatment has to be eliminated.

4.2 Estimation Strategy

To cope with the problem of selection into treatment, I apply propensity score matching (PSM) that generally provides high order of internal validity (Nichols, 2007). Regarding the measurement of the difference in spending between innovators and non-innovators at the POS, I define the potential outcome $TRANSR_{ij}(I_{ij})$ as the ratio of transactions for individual i and payment method j, where j relates to debit or credit cards, relative to every other payment instrument j′ besides j that is commonly used at the POS, and where I_{ij} equals one if individual i receives treatment (I_{ij} = 1) of payment method j and zero otherwise (I_{ij} = 0).[17]

According to Caliendo and Kopeinig (2005), the treatment effect for an individual i and payment method j can be written as

$$\tau_{ij} = TRANSR_{ij}(1) - TRANSR_{ij}(0).$$

However, the problem arises that only one of the potential outcomes is observed for each individual i, where i = 1, ..., N and N denotes the total population. Therefore, the individual treatment effect τ_{ij} cannot be estimated and one has to focus on (population) average treatment effects, which can be measured by invoking some identifying assumptions. Under the assumption that the selection into treatment solely depends on the observables X_i and the potential outcome is independent on the treatment assignment, the PSM gives consistent and efficient estimates of the average treatment effects. This is a strong assumption known as unconfoundedness or conditional independence assumption. It implies that the decision to adopt

[15] Only with strong distributional assumptions on I_{ij} and i, i.e. both parameters are normally distributed implying the effect of the treatment I_{ij} does not vary across individuals, the causal effect may be consistently estimated by OLS (Nichols, 2007). However, one can hardly think of such a homogeneous effect in reality.

[16] Some other endogeneity issues may arise since it is far from clear-cut whether the perceived characteristics of contactless payment lead to more spending or is it that the gained positive experiences of spending by contactless cards induce the perceived characteristics to raise.

[17] Other payment methods used at the POS are cash, stored-value cards, checks and money order.

contactless payment is random and exogeneous to other variables such as the number of payment card transactions. Given this assumption, the average difference in the spending ratio is thus defined as the expectation of the difference in the spending ratio of adopters and non-adopters. The parameters to be estimated are

$$\tau_{ATE|X} = E[TRANSR_{ij}(1) - TRANSR_{ij}(0)|X_i]$$
$$\tau_{ATT|X} = E[TRANSR_{ij}(1) - TRANSR_{ij}(0)|X_i, I_{ij} = 1]$$

where the ATE ($\tau_{ATE|X}$) represents the average treatment effect and the ATT ($\tau_{ATT|X}$) the average treatment effect on the treated that measures the mean effect of the treatment for the sample of innovators. This effect is more relevant in this context since individuals tend to become more and more contactless payment adopters due to the diffusion process of the innovation.

Since conditioning on all relevant covariates X_i is restricted in case of high dimensions, Rosenbaum and Rubin (1983) suggest using balancing scores such as the propensity score. It requires that all variables relevant to the probability of being selected into treatment may be observed and included in X_i. The PSM estimates in the first step each individual's probability of receiving the treatment $p(I_{ij} = 1|X_i)$, i.e. the probability of adopting contactless payment for payment method j, conditional on the observables X_i, and matches individuals with similar predicted propensities $\hat{p}(X_i)$ in the second step. This allows the untreated units to be used to construct an unbiased counterfactual for the treatment group. Based on the propensities provided by Logit or Probit estimation, the ratio of spending of seemingly similar individuals is then compared and averaged. The PSM estimators for $\tau_{ATE|X}$ and $\tau_{ATT|X}$ then result in

$$\widehat{ATE} = \hat{\tau}_{ATE|X} = \frac{1}{N}\sum_{i=1}^{N} \frac{[I_{ij} - \hat{p}(X_i)]TRANSR_{ij}(I_{ij})}{\hat{p}(X_i)[1 - \hat{p}(X_i)]},$$
$$\widehat{ATT} = \hat{\tau}_{ATT|X} = \frac{1}{N_1}\sum_{i=1}^{N_1} \frac{[I_{ij} - \hat{p}(X_i)]TRANSR_{ij}(I_{ij})}{1 - \hat{p}(X_i)},$$

whereas N_1 equals the number of innovators. The estimators are the mean differences in outcomes weighted by the propensity score.

Another requirement besides the conditional independence assumption is the overlap assumption ensuring that individuals with the same X_i have positive probability of both adopting and non-adopting contactless payment, such that $0 < p(I_{ij} = 1|X_i) < 1$. This ensures to have a comparison group in the sample.

4.3 Sensitivity Analysis

If selection is not exclusively on observables, the estimator will be both biased and inefficient. In order to check if the estimates are robust and to calculate how sensitive the estimates are to unobserved variables, I estimate the Rosenbaum bounds (RB), which provide evidence on the degree to which significant results hinge on the unconfoundedness assumption that, however, cannot directly be tested because this would mean to explicitly observe variables that affect selection into treatment (Rosenbaum, 2002). The participation probability of payment innovation is given by

$$p(I_{ij}|X_i) = F(X_i\beta + \gamma u_i)$$

where I_{ij} equals one if individual i receives treatment of payment method j and zero otherwise, X_i are the observed characteristics for individual i, F is the cumulative density function, u_i is the unobserved variable and γ is the effect of u_i on the participation decision into treatment. The log-odds ratios $p(I_{ij}|X_i)/p(I_{kj}|X_k) = 1$ for matched individuals with the same characteristics $X_i = X_k$ if there is no hidden bias, γ = 0, implying that the participation probability is exclusively determined by X_i and there is no unobserved variable that simultaneously affect the probability of receiving treatment and the outcome variable. However, two individuals with identical X will have different chances of treatment if there is hidden bias, γ > 0, so that the log-odds will be $p(I_{ij}|X_i)/p(I_{kj}|X_k) \neq 1$. In fact, the sensitivity analysis evaluates how changing the values of γ affects inference of the treatment effect while the RB are the bounds on the odds ratio that either of the two matched individuals will receive treatment (Rosenbaum, 2002).

5 Estimation Results

First, to estimate the effect of contactless payment on the ratio of spending, I obtain the propensity score of adopting contactless credit or debit cards separately for each individual, where contactless payment adopters represent the treatment and non-adopters the control group. Second, I compare the share of credit and debit card transactions to the total POS transactions of individuals in the treatment and control group with the same propensity scores and average it over the whole sample N and subsample N_1 resulting in the ATE and ATT. The results of the ATT are of more interest in this context. I thereby apply the Stata module *psmatch2* to implement PSM, which is provided by Leuven and Sianesi (2003).

Regarding the inclusion of optimal covariates in the propensity score model, only those that are unaffected by participation should be considered, i.e. they should be time invariant or measured in advance of the treatment (Caliendo and Kopeinig, 2005). According to theory (e.g. Venkatesh et al., 2003; Rogers, 2003) and previous research on contactless payment (Fujiki and Tanaka, 2009; Lee and Kwon, 2002; Wang, 2008), I estimate two Logit models separately for contactless credit and debit cards that control for demographics, financial status, perceptions on card attributes, personal innovativeness, the number of cash withdrawals and residential states.[18] The corresponding link tests indicate that the Logit models are properly specified.

The marginal effects of the Logit estimations both for contactless credit and debit cards are displayed in Table 7. It is observable that the number of cash withdrawals, education, some income and age brackets as well as certain perceptions and whether being single and having adopted mobile banking are statistically significant effects in describing the adoption of contactless credit cards, holding all else constant. The probability of adopting contactless credit cards is for individuals earning between 75000 and 99000 USD 7.2 percent higher than for those earning 100000-125000 USD

[18] For more details on the theoretical background, see section 2.

and 11 percent higher for people aging 25-34 compared to fewer than 25 years. Singles and college graduates are less likely to adopt contactless payment compared to widowed (-9.3 percent) and lower than high school graduates (-16.4 percent), respectively. A one percent increase in the number of cash withdrawals lowers the probability of adopting contactless credit cards by 2.2 percent, whereas the adoption of mobile banking raises the probability by 4.4 percent. This may give evidence that personal innovativeness has a crucial effect on the adoption behavior of innovations. As convenience of credit cards in relation to all other payment methods increases, individuals are more likely to adopt contactless credit (21 percent). This is a strong indicator that contactless credit cards may meet this requirement.

Table 7: Logit Propensity Score Marginal Effects

	Contactless Credit		Contactless Debit	
	Mfx	Std. Err.	Mfx	Std. Err.
Income (in 1000)				
<25	0.075*	-0.043	0.094*	-0.052
25-49	−0.002	-0.038	0.017	-0.049
50-74	0.043	-0.032	0.03	-0.047
75-99	0.072**	-0.034	0.015	-0.05
>125	0.058	-0.037	0.036	-0.051
Education				
High School	−0.167***	-0.052	−0.133**	-0.052
Some College	−0.151***	-0.053	−0.173***	-0.054
College	−0.164***	-0.056	−0.232***	-0.06
Post Graduate	−0.110*	-0.056	−0.252***	-0.061
Age				
25-34	0.110*	-0.063	0.165***	-0.058
35-44	0.071	-0.067	0.166***	-0.06
45-54	0.035	-0.066	0.136**	-0.061
55-64	0.014	-0.069	0.095	-0.065
>65	−0.059	-0.077	0.035	-0.075
Employment				
Working	−0.016	-0.036	0.036	-0.039
Retired	0.036	-0.045	0.049	-0.044
Others	−0.033	-0.036	−0.004	-0.038
Marital Status				
Married	−0.008	-0.039	0.00	-0.052
Separated	−0.030	-0.042	0.038	-0.061
Single	−0.093*	-0.051	0.005	-0.062
Perception				
Security	−0.021	-0.076	−0.122	-0.096
Setup	0.008	-0.143	0.182	-0.197
Acceptance	−0.118	-0.234	0.426*	-0.23
Cost	0.031	-0.118	0.307**	-0.156
Records	−0.012	-0.134	−0.192	-0.156
Convenience	0.210*	-0.125	−0.029	-0.139

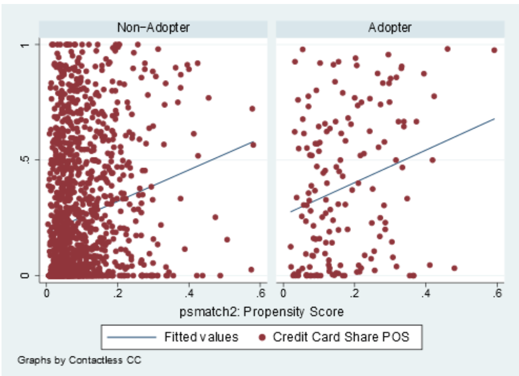
Others				
Male	0.013	-0.02	0.005	-0.023
log(Assets)	−0.002	-0.005	0.007	-0.006
CC Revolver	0.012	-0.02	−0.046**	-0.022
HH Members	−0.007	-0.008	0.009	-0.008
Mobile Banking	0.044*	-0.027	0.107***	-0.028
log(Cash WD)	−0.022**	-0.01	0.045***	-0.011
Observations	1565		1466	
Pseudo-R2	0.219		0.302	
log(likelihood)	-18377		-18470	

Note: Average marginal effects. Survey weights used. Significance levels 1% ***, 5% **, and 10% *. Base category for income is between 100000-125000 USD, for education is lower than high school, for age under 25, for employment unemployed and for marital status widowed. For brevity, coefficients of residential state dummies are not displayed

I find evidence that education, younger cohorts, low income individuals, certain perceived attributes, the number of cash withdrawals and whether to revolve on credit cards are, ceteris paribus, statistically significant factors that predict the adoption of contactless debit cards. For instance, people that attended college are 23 percent less likely to adopt contactless debit cards compared to lower than high school attendants. As costs of debit cards decrease and acceptance increase, the probability to adopt contactless debit rises by around 30 and 42 percent, respectively, implying the importance of supply-side factors. Credit card revolvers are 4.6 percent less likely to adopt contactless debit, which may suggest that these heavily rely on the provisioning of credit, which debit cards cannot provide. Also, a one percentage increase in cash withdrawals rises the probability to adopt contactless debit by 4.5 percent indicating some complementarity between cash and debit cards. As opposed to theory, gender does not have any influence on the adoption patterns of contactless payment.

The relationship between the spending ratio and the propensity score for innovators and non-innovators both for credit and debit cards is depicted in Figure 3 and 4. It can be inferred that as the propensity score increases, adopters have a higher ratio of transactions. This relationship is slightly stronger for contactless credit adopters than non-adopters (0.7 vs. 0.67) while for contactless debit adopters, the correlation is less pronounced (0.13 vs. 0.79).

Figure 3: Spending vs. Propensity Score of Contactless Credit Cards



Note: Logit propensity score, share of credit card payments at the POS

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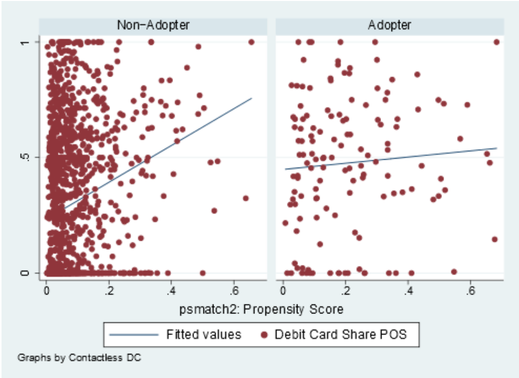
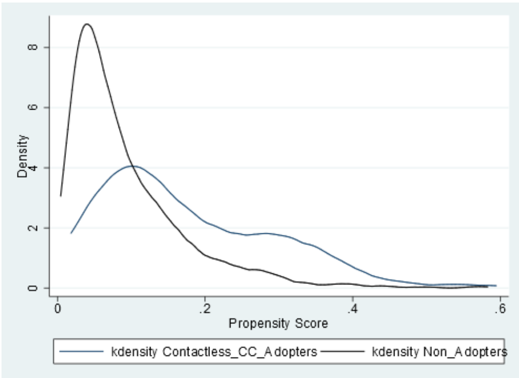
Figure 4: Spending vs. Propensity Score of Contactless Debit Cards



Note: Logit propensity score, share of debit card payments at the POS

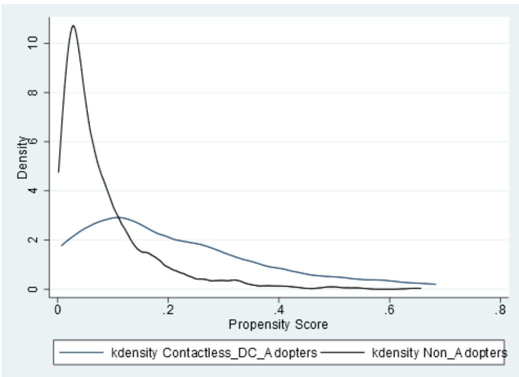
Common Support. Figure 5 and 6 exhibit the distribution of the propensity scores of contactless payment adopters and non-adopters both for credit and debit cards. They visually show that the common support assumption is fulfilled. It is also worth noting that the identified heterogeneity between these two groups, which is discussed in section 3.2, is recognizable. Thereby, the majority of cases of the control group concentrates on the interval from 0 to 0.1, where those of the treatment group mostly lie above 0.1. Consequently, individuals differ in the covariates being used in the analysis.

Figure 5: Common Support for Contactless Credit Cards



Note: Logit propensity score

Figure 6: Common Support for Contactless Credit Cards



Note: Logit propensity score

Matching Quality. To test whether unequally distributed covariates between the groups are in sum well balanced by the propensity score, I present test statistics of the matching quality in Table 8. After matching, significant differences between the control and treatment group should not be observable anymore. There are various matching algorithms, from which I choose kernel matching due to many comparable untreated individuals (Caliendo and Kopeinig, 2005). The test statistics show that the Pseudo-R^2 is close to zero and statistically insignificant in all cases, implying that none of the covariates is suitable to predict participation anymore. Further, the mean bias before and after matching indicates strong matching quality since the bias is reduced below 3 percent in all cases.[19]

Table 8: Matching Quality

	Pseudo-R^2	Mean Bias
CC POS	0.002 (0.067***)	1.7 (12.0)
CC Retail	0.004 (0.110***)	1.4 (9.3)
CC Services	0.002 (0.066***)	1.7 (11.7)
DC POS	0.004 (0.119***)	2.4 (17.2)
DC Retail	0.004 (0.118***)	2.5 (17.5)
DC Services	0.003 (0.120***)	2.1 (17.3)

Note: Significance levels 1% ***, 5% **, and 10% *. After matching, the likelihood-ratio test is not significant indicating that the regressors cannot predict participation into treatment anymore, i.e. good matching quality. Figures before matching are in parentheses.

Results. The results of the treatment effects of contactless payment on the spending ratio of different transaction types are presented in Table 9. As a reference point - besides PSM estimation -the ATE and ATT are additionally calculated using Tobit estimation that accounts for data censoring at zero, but does not consider non-random assignment into treatment. These parameters are obtained by the basic regression equation in section 4.1. The statistical significance of the ATT in the PSM estimation is calculated with the bootstrapping method as proposed in Lechner (2002), because also the variance due to the propensity score and the imputation of the common support, besides the variance of the treatment effect, has to be considered to estimate standard errors.[20]

[19] A bias reduction below 3 or 5 percent is considered to be sufficient (Caliendo and Kopeinig, 2005).
[20] The standard errors are not available for the ATE.

Table 9: Impact of Contactless Payment Cards on the Spending Ratio

	ATE_{Tobit}	ATT_{Tobit}	ATE_{PSM}	ATT_{PSM}
CC POS	0.096 (0.076)	0.131 (0.032)	0.080 (-)	0.083 (0.027)
CC Retail	0.074 (0.065)	0.094 (0.032)	0.047 (-)	0.048 (0.019)
CC Services	0.020 (0.050)	0.049 (0.024)	0.031 (-)	0.035 (0.014)
DC POS	0.239 (0.086)	0.158 (0.010)	0.144 (-)	0.100 (0.029)
DC Retail	0.120 (0.079)	0.099 (0.028)	0.085 (-)	0.045 (0.023)
DC Services	0.142 (0.050)	0.105 (0.012)	0.052 (-)	0.045 (0.015)

Note: Tobit and PSM-kernel matching estimates are provided. Standard errors in parentheses, but are not available for the ATE. Survey weights are used for Tobit estimation.

Overall, I find that contactless payment has a positive impact on the spending ratio of credit and debit card POS payments, both of retail and services payments (see Table 9). Comparing the results of the OLS and PSM estimation leads to the conclusion that self-selection into contactless payment is evident since the effects are throughout higher in the Tobit estimation (with the exception of the ATT_{Tobit} for credit card services payments). Henceforth, I focus on the discussion of the results of the PSM estimation with special attention on the ATT.

The results of the ATT are statistically significant except for debit card retail transactions (see Table 10 for significance testing). The ATE and the ATT are very similar for credit cards while they differ for debit cards with the ATT being less pronounced. The ATT of contactless credit cards on the spending ratio is associated with an increase of 8.3 percent, of which 4.8 percent stem from retail and 3.5 percent from services payments, respectively. The ATT of contactless debit cards is 10 percent while the effect is similar for retail and services payments (4.5 percent). The results imply that an average contactless credit card adopter, who makes roughly 17 credit card transactions at the POS within a month and with a spending ratio of 36 percent, increases the number of credit card transactions to approximately 21 payments under the assumption of constant overall POS payments. An average contactless debit card adopter with a spending ratio of around 48 percent and 24 monthly debit card payments raises the corresponding transaction volume by 5 transactions to 29 payments, holding total POS payments constant. Consequently, an average debit card innovator increases fee turnover of debit card issuers by roughly 7 USD per year.[21]

5.1 Sensitivity Analysis

Table 10 displays the results of the sensitivity analysis, which are provided by the Rosenbaum bounds. Since potential overestimation of the true treatment effects is suspected due to positive selection, the upper bound significance levels are reported.

[21] Assuming an interchange fee of 0.12 USD per transaction.

The test statistics show under the assumption of no hidden bias ($\gamma = 0$ or $\Gamma = 1$, respectively) that the treatment effects are statistically significant indicating that no selection bias occurs, i.e. those who have a contactless feature do not have higher spending ratios even without participating with the exception of debit card retail payments.[22] Further, the results reveal that the treatment effects for credit and debit card POS payments are still significant even if a confounding factor would alter the odds of the adoption of contactless credit cards ($\Gamma = 1.25$) and debit cards ($\Gamma = 1.5$). The upper bound Hodges-Lehman point estimates indicate that in case of $\Gamma = 1.25$, the treatment effect for credit and debit card POS payments is still 4.7 and 7.4 percent, respectively.

Table 10: Rosenbaum Bounds Sensitivity Analysis and Significance Test

	1	1.25	1.5	1.75	2	Std. Err.$_{ATTPSM}$
CC POS	0.001 (0.078)	0.038 (0.047)	0.206 (0.023)	0.494 (0.000)	0.752 (-0.021)	0.045**
CC Retail	0.026 (0.035)	0.229 (0.014)	0.591 (-0.005)	0.854 (-0.021)	0.962 (-0.033)	0.019***
CC Services	0.059 (0.021)	0.356 (0.005)	0.726 (-0.009)	0.923 (-0.018)	0.984 (-0.027)	0.014**
DC POS	0.000 (0.106)	0.008 (0.074)	0.061 (0.048)	0.206 (0.024)	0.423 (0.005)	0.032***
DC Retail	0.124 (0.025)	0.483 (0.001)	0.807 (-0.017)	0.949 (-0.033)	0.990 (-0.046)	0.036
DC Services	0.005 (0.037)	0.074 (0.020)	0.288 (0.007)	0.575 (-0.003)	0.798 (-0.011)	0.078***

Note: Upper bound significance levels are displayed (p-values). Upper bound Hodges-Lehman point estimates are in parentheses. Standard errors for the PSM estimation of the ATT are calculated using 100 bootstrap replications taking into account the propensity score while for the ATE it is not applicable.

6 Conclusion

The aim of this paper was to investigate the effect of contactless payment on spending in terms of transactions for different transaction types at the point-of-sale using a comprehensive US data set (SCPC). Controlling for selection into treatment by propensity score matching, my analysis reveals that recent retail payment innovation such as contactless credit and debit cards lead to an increase in the spending ratio by roughly 8 and 10 percent for credit and debit cards, respectively. The results are insensitive to any hidden bias.

The results provide evidence that faster and more convenient payment products that can be deployed at the POS such as contactless payment induce individuals to undertake more frequent transactions. These findings give advice for contactless card issuers to actively promote the payment product and thus accelerate the diffusion process, which finally is expected to lead to increasing revenue streams. Also, they show that policy makers should pay attention on regular market monitoring to ensure balanced fee structures in the payment market, as more frequent transactions put higher burdens on shop owners. Under the current interchange fee structure, for

[22] Note that $\Gamma = e^{\gamma}$.

instance, incremented costs for merchants due to more frequent debit card usage cannot be compensated by the reduction in costs due to faster checkout.[23]

The analysis faces several limitations. First, the major downside of the data set entails the absence of information on the exact spending in terms of volume and value of contactless devices. It only reports their adoption rate. In fact, there may exist two different and independent processes determining the adoption in the first and the usage of contactless payment in the second stage. For instance, contactless payment adopters could never use the technology, but instead pay more frequently by conventional payment cards than those who do not possess a contactless card, resulting in a possible overestimation of the corresponding effect. Payment diaries that report each transaction in detail would help to obtain more accurate results. Additionally, the effect on value spending could then be investigated.

Second, the data set does not obtain supply-side factors that obviously play a crucial role in the context of individual payment preferences. In this sense, the question raises how generalizable the setting of the empirical study and the results are. There are major cultural and institutional differences between the US and European payment composition at present stemming from history. High actual payment card usage in the US can be traced back to the historical reliance on check use in conjunction with an undeveloped giro system whereas the importance of credit transfers and debit cards in Europe originated from the historical establishment of the postal giro system. There seems to be a predominant inertia in payment instrument use and the current patterns depend strongly on the past composition (Humphrey et al., 1996). Therefore, specific payment patterns in the two payment areas may have a significant impact on the strength of the effects. Also, the US may experience greater network effects since the diffusion of contactless payment terminals is already at an advanced stage.

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[23] Given the fee of 0.12 USD and the reduction of 0.03 USD per transaction (cf. Board of Governors of the Federal Reserve System, 2011; Borzekowski and Kiser, 2008).

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