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NETWORK EFFECTS AT RETAIL PAYMENTS MARKET: EVIDENCE FROM RUSSIAN INDIVIDUALS

Abstract:

This research empirically evaluates the effect of network externalities for individuals behavior at Russian retail payments market. Specifically, the effects of direct and indirect network externalities for cardholding and usage probabilities are examined. Using the representative sample of 1500 individuals from all Russian regions this study finds significant robust evidence of positive association between the degree of both types of network externalities and individuals' activity at the Russian retail payments market. Results are economically significant: a standard deviation increase in network effects leads to 2.5-4 percentage points increase in probability of cardholding and usage. Findings imply that one needs to account for network effects which play an important role for the payment behavior before implementing payment stimulating programs in Russia aimed at cardholders or users.

Keywords:

Retail payments; payment cards; network effects; cardholders' behavior; financial services

JEL Classification: G21, D53, E42

1 Introduction

There is an obvious tendency towards cashless economy in the modern world. From the one side, financial regulators benefit from it and tend to stimulate the development of this phenomenon both at the individual users' and the national levels. On the other hand, apart from the government, other market participants actively participate in the non-cash payments proliferation. However, despite these existing efforts Russia is still not considered to be in the cashless economy (Krivosheya, Semerikova, Korolev & Tarusova, 2018) that is why there is still a potential to further foster retail cashless payments.

The card retail payments market is organized as a two-sided market. In order to settle the payment by payment card, it is necessary to involve two groups of end-users: buyers (cardholders) and sellers accepting cards (merchants). Unlike merchants, who choose only whether to accept cashless payment instruments for the purchases of goods and services, cardholders have two decisions to make at the retail payments market. First, they choose whether to hold the card and, then, whether to use it as a payment instrument.

The share of Russian individuals that hold at least one card is close to those in the developed and more active retail payments markets (according to the National Financial Research Agency (NAFR) as at 2016 about 73% of Russian individuals own at least one payment card[1]). At the same time, the usage of payment cards has significantly improved over the last few years. During the last 8 years the share of cashless transactions in total number of transactions increased from 21% to 71%.[2] Despite this, there is still significant share of users, who prefer cash and the habit of using it for transactions is still strong (Plaksenkov, Korovkin & Krivosheya, 2015). Although some stimulating measures for the cashless economy development have been efficient, the effect of government policy on retail payments market development is still limited (Krivosheya, Korolev & Plaksenkov, 2015). Part of this result might be explained by the presence of network externalities, which cannot be explicitly affected by the stimulating proposals and initiatives.

Network externalities impact both the decisions of cardholders and the choice of merchants. In this study we will focus on the behavior of cardholders only. Network effect is simply a positive effect which occurs when the utility that a user extracts from consumption of the product or service increases with the number of other agents consuming the same product or service. There are two types of network externalities in the retail payments market for cardholders due to the two-sided nature of the retail payments market. Direct network externalities show how the probability to hold and use a card by an individual depends on the decisions of other cardholders to hold and

[1] http://www.banki.ru/news/lenta/?id=9493554

[2] https://vedomosti.ru//finance/articles/2017/03/14/681000-oplachivat-kartami

use payment cards. Indirect network effect, similarly, shows how the intention to hold and pay by card depends on the level of card acceptance by merchants. Therefore, the main purpose of this study is to analyze empirically the effect of both types of network effects for cardholding and card usage demands in Russia. Russian market is characterized by the high role of cash, which may undermine the effect of some mechanisms behind the influence of the network effects. In order to understand the mechanisms behind the link between the network externalities (effects) and the probability of card holding and usage we use the concept of net benefits. Net fixed benefits are associated with cashless instrument holding compared to cash holding less any costs attributed to the cashless payment methods holding compared to the cash based ones. Net variable benefits appear during the cashless instruments usage and represent benefits from using a card compared to cash net of any costs appearing from card usage instead of cash. An individual chooses to hold the card and pay by it if the net fixed benefits and net variable benefits are respectively greater than zero. Network externalities may change the value of the net benefits.

Direct network externalities that result from the increased activity of individuals (in terms of cardholding and card usage) increase both net fixed and net variable benefits. The key mechanisms outlined in the subsequent section of this paper include psychological reasons, improvement of the quality of banking services, reduction of the cardholding and usage fees as well as the improvement of stimulating programs as a result of increased number of cardholders and card users. Indirect network effects, associated with the higher acceptance rate at the merchants' side of the market, also increase both types of benefits, mainly via the increased payment products diversity, improved loyalty programs and payments related innovation. Therefore, outlined theoretical mechanisms suggest that both the direct and indirect network externalities are positively correlated to the probability of holding and using cashless payments by Russian individuals.

This research aims to contribute to the rising literature on the determinants of cashless payments instrument holding and usage (Arango-Arango, Bouhdaoui, Bounie, Eschelbach, & Hernandez, 2018; Bagnall et al., 2014; Bounie & Francois, 2006; Bounie, François, & Hove, 2016; Carbó-Valverde & Liñares-Zegarra, 2011; Gresvik, 2008). Factors that have been heavily investigated include transaction characteristics (e.g., cost of the purchased goods / services, type of goods, day of the week), merchant's (store type, size, etc.) and socio-demographic characteristics (income, education, age, sex, employment status etc.). However, most of the studies do not investigate the presence of network externalities for the customers empirically and those that do never distinguish between direct and indirect network externalities. These two types of network externalities affect the behavior of the individuals via different mechanisms and, hence, need to be separated in the empirical research.

Besides, none of the articles outline the network externalities on Russian retail payments market, which exhibits high role of cash that might alleviate the effect of network externalities even nowadays (Plaksenkov, et al., 2015). Finally, none of the

studies provide empirical investigation of the effects of network externalities on the cardholding probability and study the effect only on the usage. There are a few limitations to such approach: first, when treated independently from cardholding probability, card usage probability estimations might produce the selection bias problem as the data is available only on those individuals that already own a card; second, the mechanisms underlying the network externalities effect on the cardholding probability are largely ignored, however, these are different in theory (Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016; Rochet & Tirole, 2003, 2006). This study aims to feel these gaps by empirically analyzing the effect of network externalities at Russian retail payments market in the context of cardholding and card usage probabilities of an individual.

After analyzing the literature, this is the first study to provide the empirical investigation into the effect of network externalities for the Russian retail payments market. To the best of the knowledge, only Krivosheya and Korolev (2016) study the characteristics of the cardholding and card usage of Russian individuals. Their study, however, focuses on the aggregate notion of cardholders' benefits from the participation in the retail payments market and does not provide any investigation into the effect of the network externalities on individuals' payment behavior. This research aims to fill this gap by providing empirical analysis of the effect of network externalities on the cardholding and card usage probabilities at the Russian retail payments market. Also, this study is the first to investigate the effect of network externalities on the cardholding probability separately from the card usage probability. Although the card usage is found to be affected by the network externalities at the developed markets (Arango-Arango et al., 2018; Bounie & Francois, 2006; Bounie et al., 2016) the cardholding decision is a prerequisite for the card usage. Cardholding demand is formed on the basis of fixed rather than variable benefits, which changes the mechanisms of influence of other variables on this demand (Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016). The effect of network externalities, hence, might be different for this probability.

The results of the study are important from the practical point of view because they help to understand the degree of potential influence different stimulating measures might have on the behavior of the individuals at the retail payments market, in particular, cardholding and usage. The effect of network externalities cannot be explicitly changed by any stimulating programs or other government and private sector intervention. Therefore, there is some probability that can not be altered by any financial market policies. It would be valuable for the practitioners related to the development of the financial services market such as the Central Bank of Russia, commercial banks and payment systems to understand the degree of influence they can have on the individuals at the retail payments market. Besides, understanding the degree of network effects contributes to the understanding of the organic market growth resulting from the multiplicative effect of increased payment activity across two market sides.

Using the representative sample of 1500 individuals from all Russian regions this article finds significant and robust evidence in favor of positive correlation between the degree of network externalities and individuals' activity at the retail payments market. Increased share of merchants that accept payment cards increases the probability that each cardholder holds payment card and pays by it for goods and services. This result stays unchanged despite the measure of network externality used. Similar results are obtained for the direct network externalities both at the regional and federal region levels: increased share of cardholders and card users increases the probability that each cardholder holds the credit cards and pays by it.

These results are significant not only from the statistical point of view but also from the economic point of view. One standard deviation increase in the average federal region card acceptance by merchants increases probability of card holding by 3.79 percentage points and card usage by 2.41 percentage points. Direct externalities have similar effect: one standard deviation increase in the average federal region usage rate of payment cards increases the probability of card holding by 2.9 percentage points and using by 3.34 percentage points. Combined, one standard deviation increase in the factor reflecting both network externalities at the federal region level increases the probability of card holding by 3.13 percentage points and using by 3.96 percentage points. In comparison, being a high income instead of middle income individual increases card usage probability by 2.9 percentage points, while having beginning professional education increases the probability of cardholding by 8.33 percentage points in comparison with only school.

Following this introduction, there are five sections in this work. In the subsequent section, the theoretical mechanisms of the effect of direct and indirect network externalities on cardholders' holding and usage probability will be explained. The third section explains empirical set-up which consists of data, empirical model description and the estimation method. Section 4 explains the main results from statistical and economical outlook. Section 5 concludes, identifies limitations and outlines directions for further research.

2 Theoretical framework

The aim of this study is to analyze the effect of network externalities (effects) on the probability of card holding and usage in the retail payments market. In general, network effect occurs when the utility that a user extracts from consumption of the product or service increases with the number of other agents consuming this product or service. In the context of the retail payments market this effect can be separated into direct effect or indirect effect according to Katz and Shapiro (1985). In other words, the goal is to analyze how direct and indirect network externalities separately affect the probability of card holding and usage.

Direct network effect can take different forms in the framework of merchants and cardholders. If we focus on the cardholders, we analyze how the value of net benefits of one cardholder associated with the cardholding and card-usage is affected by the

total activity of other cardholders. In contrast, if we looked at the merchant side of the market, we would analyze how one merchant is affected by the total share of cashless payments accepting merchants. In the work we concentrate on the cardholders' side of the market and, hence, investigate the former relationship.

Indirect network effect can also take several forms in the same framework as before. If we focus on the cardholders, we would like to analyze how a cardholder is affected by the retail payments activity of merchants. In contrast, if we looked at the merchants' side of the market, we would analyze how a merchant's accepting benefits are affected by the activity of the cardholders. Due to the focus of this study on the cardholding side of the market, this work focuses on the former definition of the indirect network effects.

A decision to hold and use a payment card by an individual is based on the relative size of his benefits and costs associated with holding and using cashless payments (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Bolt & Chakravorti, 2008; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002, 2003, 2006). In any model of the retail payments market equilibrium, an individual chooses to engage in the market if the size of the net benefits (benefits associated with cashless payments compared to cash payments less any costs attributed to the cashless payment methods compared to the cash-based ones) exceed zero (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Guthrie & Wright, 2007; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002; Wright, 2004). Direct and indirect network effects can change the size of the benefits and fees (Bedre-Defolie & Calvano, 2013; Bolt & Chakravorti, 2008; Krivosheya & Korolev, 2016). To begin with, it is important to define both concepts in the context of the work.

Benefits are rewards for cardholders from the holding card and its usage compared to the holding and using cash instead. Individuals, unlike merchants, make two decisions at the retail payments market: first, they choose whether to hold a card and, then, they choose whether to use a card for payments for goods and services (e.g., Baxter, 1983; Bolt & Chakravorti, 2008; Krivosheya & Korolev, 2016). That is why, benefits are usually separated into fixed and variable (Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016). Variable benefits *(b)* represent the benefits arising from each particular transaction. Due to the nature of such benefits, variable benefits arise only in case of card usage. Such benefits may be manifested, for instance, in the form of increased speed of transactions, satisfaction from paying with card compared to cash, ability to defer payments, declined risk of fraud or easier personal financial management (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Grauwe, Paul, & Rinaldi, 2002; Guthrie & Wright, 2007; Krivosheya & Korolev, 2016). Fixed benefits *(B)* represent the benefits from issuing and holding a card instead of holding alternative methods of payment (e.g., cash or cheques). They, therefore, do not depend on the number of transactions. These benefits are associated with the cardholding demand. The examples of fixed benefits include the improved security and protection against robberies and the ability to consume larger amounts due to easier usage (e.g., no withdrawal costs, no need to calculate the necessary amount of cash holdings before

transactions) (Bedre-Defolie & Calvano, 2013; Grauwe et al., 2002; Hunt, 2003; Krivosheya & Korolev, 2016).

Fees or costs are tariffs set by banks for cardholders for holding (issuing) a card and its subsequent usage. Similarly to the benefits, the fees are also separated into fixed and variable. Variable fees *(f)* are the payments charged by the bank per transaction. Whereas usually in theory this payment is non-negative in Russia it is negative since the issuing banks usually offer cardholders some forms of stimulating programs (e.g., bonuses, cashback) for making payments by card (Chernikova, Faizova, Egorova, & Kozhevnikova, 2015; Chizhikova, 2013; Krivosheya & Korolev, 2016). Fixed fees *(F)* are the payments for card issuance and service, which are independent of the number of transactions (for example, annual service fees) (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016).

In this context, a person will issue a card if his/her fixed benefits (*B*) are greater than the costs of issuing a card (*F*), i.e. *B>F*. A person will use the card for payments for goods and services if her/his variable benefits *(b)* are greater than the variable costs of using the card *(f).* That is, *b> f*. Network externalities may affect the value of all these four parameters, thereby altering the demand for cardholding and card usage. In the subsequent subsections we will outline possible underlying theoretical mechanisms that explain how each of the two network effects impacts the probability of holding (fixed net benefits) and using (variable net benefits) cards in the retail payments market.

Direct network effects

The direct network effects, in the context of this study, result from the increased activity (cardholding and card usage) of the cardholders. In other words, the direct network effects are associated with the increase in the quantity demanded for the issuing bank services. In this case, banks are more inclined to give interest on the remaining account balances and other bonuses (e.g., vip passes to the airport lounges, concierge services, etc.) for holding money on the card account when the number of cardholders rise (Borzekowski, Elizabeth, & Shaista, б. д.; Ching & Hayashi, 2010; Hayashi, 2008; D. B. Humphrey, 2010). Such effect arises from the nature of issuing banks competition. In case of few cardholders, issuing banks can easily segment the potential cardholders and find its own niche among the individuals without payment cards (Hasan, Schmiedel, & Song, 2012; Meadows & Dibb, 1998; Todd & Lawson, 2003). Segmentation of the potential customers allows issuers charging higher fees than in case of the competition for existing cardholders with other issuing banks (Hasan et al., 2012; Todd & Lawson, 2003). The quality of services and the level of fees are among the key factors for choosing a bank for cardholders (Arango-Arango et al., 2018; Bagnall et al., 2014; Borzekowski et al., 2008.; Bounie & Francois, 2006; Bounie et al., 2016). Taking this fact into the account, issuing banks are likely to change the quality of services without increasing the fees levied on the individuals or decrease the fees without decreasing the quality of services (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Hasan et al., 2012; Rochet & Tirole, 2002). In

Russia, issuing banks started to show these particular patterns of behavior during the recent years (Chernikova et al., 2015; Chizhikova, 2013; Krivosheya & Korolev, 2016). In either of these two cases (quality increase or fees decrease), individuals will enjoy the higher value of net benefits, therefore, the more people possess payment cards, the higher is the probability of cardholding demand.

Another important factor for the size of fixed individuals' benefits is the perception of payment cards holding (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016). Payment card, especially of premium type, may be considered as a signal of status (Arango-Arango et al, 2018; Roberts & Jones, 2005; Souvignet et al, 2014). In case few people in a particular region own a payment card, the signal is likely to be ignored by the peers in a group (Arango-Arango et al., 2018; Souvignet et al., 2014). Similarly, the larger the share of cardholders, the more likely other cardholders are to recognize the difference between payment instrument types. Besides, cardholders are subject to the herding behavior: once an individual sees that other individuals own payment cards, she/he associates it with smaller risks, higher benefits and, overall, more positive experience (Bagnall et al., 2014; Darban & Amirkhiz, 2015; Shy, 2011). Therefore, the more people hold and use cards the more is each individual likely to become a cardholder.

Finally, an increase in the share of cardholders leads to higher payment systems' spending on anti-fraud systems and other issues of security because of the economies of scale present in the industry (Kadhiwal & Zulfiquar, 2007; Kim, Tao, Shin, & Kim, 2010). Security of cashless payments has been an issue of particular focus for the payment systems during the last decades due to the increase of cyberrisks and data breaches (Kim et al., 2010). As a part of the response, payment systems started to invest in the anti-fraud systems more heavily, especially in the regions of higher cashless usage and holding. This also led to the standardization of the fraud management systems in banks (Kadhiwal & Zulfiquar, 2007; Kim et al., 2010). Therefore, the more people have cards, the more each individual is willing to hold cards as the security investments and monitoring are more heavily funded.

Krivosheya and Korolev (2016) empirically evaluate the benefits and fees of the individuals at Russian retail payments market. They found that the level of net fixed individual benefits is greater than zero, hence, the decision to hold payment card is associated with the larger amount of benefits rather than the costs. They also hypothesize that part of this result might be explained by the network externalities. Overall, all of the mechanisms outlined above suggest that the direct network effects should be associated positively with the cardholding demand. The first hypothesis is, therefore:

H1: The probability of cardholding increases with larger share of cardholders and users of cashless payments.

In order to investigate the effect of direct network externalities on the card usage demand by the cardholders we need to analyze how increased number of cardholders

and card users affects net variable benefits. Similarly to the arguments above, an increase in the share of the card users and cardholders is equivalent to the increase in the quantity demanded for the issuing banks' services. Similarly to the case with the interest on account balances, issuers are more likely to provide cardholders with loyalty (e.g., cashback and bonus) reward programs or other stimulating measures activated per each transaction (Bedre-Defolie & Calvano, 2013; Carbó-Valverde & Liñares-Zegarra, 2011; Hasan et al., 2012; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002). When the number of cardholders and card users is small, the issuers can easily segment the market of potential cardholders and card users and charge them higher fees or provide lower quality of services (Hasan et al., 2012; Meadows & Dibb, 1998; Todd & Lawson, 2003). Once the number of cardholders rise, issuing banks start to compete for the existing card users with other issuers, thereby improving the quality of services without altering the fees or by charging lower usage fees (providing better stimulating programs and cashbacks) without changing the quality of basic services (Bedre-Defolie & Calvano, 2013; Hasan et al., 2012; Rochet & Tirole, 2002). Therefore, the more people hold and use payment cards, the more each cardholder is willing to use cashless payment instruments.

The perception of card usage by cardholder may also be altered as a result of the increased share of card users. Once a cardholder sees that more people are paying by card for the transactions, he/she thinks that it can be safer to use payment cards (Arango-Arango et al., 2018; Darban & Amirkhiz, 2015; Gresvik, 2008; D. B. Humphrey, Pulley, & Vesala, 1996). This is similar to the herding behavior outlined above. Therefore, the more people use cards, the more likely each cardholder is to begin to pay by cards.

Payment systems are found invest more funds into the processing systems to increase the speed per transaction with a larger number of cardholders (Asokan, Janson, Steiner, & Waidner, 2000; Massoth & Bingel, 2009; Teo, Ooi, Yew, Tan, & Hew, 2015). Payment systems respond to the fact that the the network becomes busier (more users — longer processing) by perpetually improving the processing infrastructure in more active regions (Asokan et al., 2000; Massoth & Bingel, 2009). In fact, they do not allow the processing speed to drop below the initial level as a result of platform competition in order not to decrease the quality of services (Asokan et al., 2000; Teo et al., 2015). Therefore, each individual is able to enjoy the benefit of faster processing speed as a result of the increased card usage demand.

More active card usage in a region fosters payments innovations (Ali, Barrdear, Clews, & Southgate, 2014; Milne, 2006; Rysman & Schuh, 2017). Payments may become more convenient as a result of these innovations (e.g., Apple Pay / Samsung Pay / Android Pay, other wallets and contactless payments, etc.) (Au & Kauffman, 2008; de Kerviler, Demoulin, & Zidda, 2016; Mas & Radcliffe, 2010; Slade, Williams, & Dwivedi, 2013; Souvignet et al., 2014; Wang, 2008). Providers of such services (e.g., issuing banks, startups, technological firms) find it profitable to enter a particular region if the number of potential users allows them to break even (Hasan et al., 2012;

Milne, 2006; Rysman & Schuh, 2017). Therefore, the more people hold and use payment cards, the more likely payment innovations are to appear and the larger is the value of benefits of each potential card user.

Finally, the higher share of the individuals engaged with the payments market may foster the creation of cardholders' associations aimed at protecting and improving the cardholders' welfare (Chernikova et al., 2015; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002). Bargaining power of such associations is usually higher than of each particular individual, which allows it to effectively protect the interests of cardholders (e.g., set pressure on tariffs -or vote against the interchange fee cuts, etc.) (Carbo-Valverde & Liñares-Zegarra, 2012; Malaguti & Guerrieri, 2014; McGinnis, 2012; Weiner & Wright, 2005). The more cardholders there are in the issuing banks' portfolios, the larger is the bargaining power of such associations and the more favorable the conditions at the retail payments market are for the cardholders. As a part of their analysis, Krivosheya and Korolev (2016) also evaluate the value of net variable individual benefits. Despite the high role of cash and habit of using cash for payments in Russia (Plaksenkov et al., 2015; Krivosheya & Korolev, 2016), as in case of the fixed benefits, these are, on average, greater than zero, hence, the decision to use payment card is also associated with the larger amount of benefits rather than the costs. Overall, all of the mechanisms outlined above suggest that the direct network effects should be associated positively with the card usage demand. The second hypothesis is, therefore:

H2: The probability of card usage increases with larger share of cardholders and users of cashless payments.

Indirect network effects

Indirect network effects in this context are associated with the higher acceptance rate at the merchants' side of the market. As in the previous section of the study, we will explain how the net fixed and variable benefits are affected as a result of the increased share of accepting merchants. First of all, payments product diversity increases as a result of higher merchants' acceptance rates. The stores can offer the co-branded cards (Arango & Taylor, 2008; Manchanda & Saqib, 2008; Worthington, 1999). This type of cards usually takes the form of a merchant's bonus or loyalty card with a payment function provided by some bank. The probability that a particular individual finds a suitable payment product from the merchant increases when the number of shops, which accept cashless transactions increase (Arango-Arango и et al., 2018; Bounie & Francois, 2006; Gresvik, 2008). Besides, the co-branded card products and co-branded loyalty programs are usually associated with better quality of loyalty programs (Manchanda & Saqib, 2008), which may translate to the higher fixed and variable benefits of the cardholders (Krivosheya & Korolev, 2016).

In addition, the overall development of the payment network resulting from higher acceptance rates is associated with the creation of more sophisticated products (payment innovations, etc.) by banks (Ali et al., 2014; Hasan et al., 2012; Milne, 2006;

Rysman & Schuh, 2017). As a result, a potential cardholder can find a product that is more suitable for her/his needs and preferences. Some banks are also likely to be both acquirers and issuers (Bolt & Chakravorti, 2008; Chizhikova, 2013; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002), hence, as a result of higher acceptance rates they may redistribute funds within the departments of the bank and promote cardholding more actively (Krivosheya, 2018). Such active promotion may, again, take the form of improved quality of services without the fee levels change or smaller fees level charged by banks for the same level of services. Net fixed cardholders' benefits are, hence, likely to be larger when higher share of merchants accept payment cards.

All in all, higher share of accepting merchants is likely to translate to higher net fixed benefits levels. In other words, indirect network externalities are likely to be positively associated with the probability of cardholding. The third hypothesis is, hence:

H3: The probability of cardholding increases with higher share of accepting merchants.

Finally, the card usage demand might also be affected by the higher share of merchant acceptance. First of all, cardholders have more chances to use cashless payments when more merchants accept cards. As a result, the option value to pay with a card increases for each particular individual, therefore increasing his/her benefits value (Bedre-Defolie & Calvano, 2013). In addition, the variable benefits can be enjoyed by the cardholder only in case there are places to use cashless payments. In case fewer merchants accept payment cards, the value of benefits for each particular cardholder becomes smaller even in the presence of high motivation and willingness to pay with a card (Baxter, 1983; Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2016; Rochet & Tirole, 2002).

Cashless payments become convenient to all of the market participants in case more merchants accept payment cards. The cashiers become more skilled and trained in case the acceptance rates are higher (knowing how to operate a POS terminal becomes a job requirement for the cashiers) (Arango & Taylor, 2008; D. Humphrey, Willesson, Lindblom, & Bergendahl, 2003; Jonkers, 2011). This improves the speed of transactions and decreases the probability of fraud at the point of sale (e.g., when the payment card is taken from the cardholder) (Arango & Taylor, 2008; Bedre-Defolie & Calvano, 2013; Krivosheya & Korolev, 2018). Besides, equipment gets more innovative when the number of merchants accepting cards increases, which further increases the benefits associated with the card paying (Ali et al., 2014; Rysman & Schuh, 2017). Therefore, the more merchants accept cards, the higher is the cardholders demand for using payment cards

Some loyalty programs are conditional on the type of merchants and particular merchant brands. For instance, some banks provide higher cashback for some merchant categories or assign more bonuses as a result of a transaction at the partnered merchants' locations (Bolton, Kannan, & Bramlett, 2000; Carbó-Valverde & Liñares-Zegarra, 2011; Ching & Hayashi, 2010). The probability that a particular store,

where an individual uses payment card, is a participant of some kind of banking loyalty program is higher when more stores accept payment cards. Hence, variable fees may be reduced (stimulating programs may be of higher quality) as a result of increased merchant acceptance rates.

To summarize, the larger acceptance shares by merchants is likely to increase the probability of card usage because of increased net variable benefits. In other words, indirect network externalities influence not only the cardholding demand but also the card usage demand of the individuals.

H4: The probability of card usage increases with higher share of accepting merchants.

General effects of transition towards cashless economy

Combined together, direct and indirect network effects are related to the overall development of the retail payments market in a country. This is equivalent to the transition towards the cashless economy. Such transition provides a number of benefits to all of the participants of the economy, including the government. In fact, Plaksenkov, Korovkin and Krivosheya (2015) find that the government enjoys one of the largest benefits from the transition to cashless economy and, therefore, has incentives to stimulate the market development.

Key benefits of the government are related to the increased transparency, higher stability of the banking sector and enhanced growth (Plaksenkov et al., 2015). Firstly, the economy is more transparent, not anonymous, so it is harder to participate in the illegal economic transactions. (Bayero, 2015; Krivosheya, Korolev and Plaksenkov, 2015; Krivosheya et al., 2017). Secondly, banking system is more stable as banks receive balances on accounts which can be used for the liquidity purposes and funding (Chernikova et al., 2015; Hasan et al., 2012; Humphrey, 2010). Thirdly, GDP grows as people spend more using cashless payment instruments, which increases the consumption (Arango-Arango et al., 2018; Bagnall et al., 2014).

Government, thus, can initiate regional or national campaigns and stimulating measures. Krivosheya, Korolev and Plaksenkov (2015) provide the analysis of such initiatives both for Russian and global markets. Governments can introduce compulsory salary cards for the budget workers, national loyalty programs, electronic payments for housing, communal services, taxes and other public services as well as national payment systems and other incentives. All of these usually result in higher merchant acceptance rates and cardholding and card using shares, which lead to the higher impact of the network effects at the retail payments market (Bounie et al., 2016; Milne, 2006; Shy, 2011). Therefore, transition towards the cashless economy may generate additional benefits for the governments, which, in turn, increase the effect of the network externalities at the retail payments market.

Commercial agents such as banks and payment systems receive benefits from the cashless economy creation as well (Krivosheya et al., 2015; Bayero, 2015; Hasan et al., 2012). They can also propose the stimulating programs in order to boost the acceptance and usage rates by merchants and cardholders (Bedre-Defolie & Calvano, 2013; Humphrey, 2010; Rochet & Tirole, 2006). For instance, banks and other financial institutions usually launch programs and events to increase financial literacy for the cardholders (Bayero, 2015; Krivosheya et al., 2015). Most of the individuals that do not own a card are afraid of the potential perceived losses and risks they associate with cardholding (Arango et al., 2018; de Kerviler et al., 2016; Gresvik, 2008; Humphrey et al., 1996). Such programs can improve the quality of information among the market participants and help boost the cashless methods usage rates, thereby further signifying the role of network externalities (Bayero, 2015; Hunt, 2003; Milne, 2006). There are also other measures to encourage the use of cards such as discounts on VAT, loyalty programs, nation-wide lotteries, etc (Krivosheya et al., 2015) all aimed at the increase of acceptance and usage rates.

The stimulating measures implemented by the public and private sector increase the likelihood that people will start to hold and use the card to pay for goods and services. Hence, they must strengthen our hypotheses. Overall, the theoretical mechanisms outlined above suggest that both the direct and indirect network externalities are positively correlated to the probability of holding and using cashless payments. However, in Russia, the role of cash and the share of the shadow economy are still large (Krivosheya & Korolev, 2016; Krivosheya et al., 2015), which may decrease the effect of the network externalities and undermine at least some of the mechanisms presented in this section. In order to test the presence and significance of the network externalities for Russian cardholders, we test the hypotheses developed above using the real market data in the subsequent sections.

3 Empirical Set-Up

Data

The main data is collected from the proprietary sources provided by the “Finance, Payments, and e-Commerce” chair established by Moscow School of Management SKOLKOVO. The chair conducted the national survey of Russian cardholders in 2013-2014. The survey is representative for the whole Russian economy as well as Russian regions and includes quotas for age, gender and regions to ensure that the valid proportion of different groups of individuals (in terms of income, age, gender and geographical area) is sampled. The survey was organized as face-to-face interviews and included the individuals who are at least 18 years old and are living in the cities with at least 500 thousand citizens. Three stage probability sampling was performed in order to guarantee sample representativeness.

The questionnaire includes sections on the individual’s payment behavior and socio-demographic profile (age, education, gender, income, location and work). The survey

also includes a separate data sample on 800 traditional (offline) merchants focused on their profile and behavior at the retail payments market. The latter is used for the calculation of indirect network effects.

The final sample for the analysis includes1500 individuals. As in official Russian statistics as at 2013-2014, 44.4% of all respondents are female, while 55.6% are male. 26.7% of the respondents are from Moscow, 11.3% from Saint-Petersburg and the rest 62% are from other Russian regions. 73.5% of all the respondents hold at least one payment card, whereas 26.5% do not have any cashless payment instruments at all. 75% of all the cardholders use cards to pay for their transactions and the rest 25% always pay by cash. In order to mitigate the selection bias problem, we include both individuals who hold and do not hold a card. Representativeness for the Russian retail payments market (major characteristics of the sample outlined above coincide with the Russian official population statistics) ensure that the selection bias is minimized. The sample is further reduced based on the availability of control variables.

Model

The key research questions are: do the network effects affect the probability to hold payment card and to use it as a payment instrument for goods and services? In order to test the hypotheses developed in previous section and answer these questions, we construct the following models for, respectively, cardholding and card usage probabilities:

$$Holding_i = \alpha + \beta * DNE_i + \gamma * INE_i + +\theta * Age_i + \tau * ED_i + \zeta * SD_i + \eta * Income_i + \phi * Travel_i + \varepsilon_i$$

$$Usage_i = \tilde{\alpha} + \tilde{\beta} * DNE_i + \tilde{\gamma} * INE_i + +\tilde{\theta} * Age_i + \tilde{\tau} * ED_i + \tilde{\zeta} * SD_i + \tilde{\eta} * Income_i + \tilde{\phi} * Payment\ characteristics_i + \varepsilon_i$$

Where i refers to each individual. $\mathrm{Holding_i}$ is a dummy variable, which gets 1 if an individual has at least one card and 0 otherwise. $\mathrm{Usage_i}$ denotes a dummy variable, which attains 1 if an individual who has a card uses it to pay for goods and services and 0 otherwise. $\mathrm{DNE_i}$ represents the vector of direct network externalities while $\mathrm{INE_i}$ represents the vector of indirect network effects. ED_i stands for the vector of education level related characteristics. $\mathrm{SD_i}$ is a vector of social & demographic characteristics of the individual. $\mathrm{Travel_i}$ denotes the vector of characteristics related to the travel frequency. $\mathrm{Payment\ characteristics_i}$ is about a vector of variables reflecting payment behavior and contract details. Finally, $\alpha, \beta, \gamma, \theta$ are the vectors of coefficients and ε_i refers to the independently identically distributed error term.

The first model is independent from the second one. In order to mitigate potential selection bias arising from the fact that the individuals can only pay with a card when they are the cardholders (i.e., Holding variable is 1 for all the potential users of the card in the sample) the second model is not independent from the first one and is rather considered as a second step in the estimations. Some unreported robustness

checks are performed with the assumption that the models are independent. Although the key results regarding the network externalities stay the same as in the main analysis, we decided to focus on the interrelated representation of the models as the tests provided in the regression outputs suggest that the models should be considered together in order to minimize selection bias. Further analysis assumes that the second model is based on the first model as a selection equation.

Dependent variables

There are two dependent variables in the analysis, one per each of the two models. The first is card holding dummy ($\overline{\text{Holding}_i}$) that takes the value 1 if the individual has at least one card and 0 if an individual possesses no payment cards. This data is available directly from the survey. The questionnaire contained the direct question: Do you own a bank payment card issued in your own name? This dependent variable is used in the first (selection) equation, which is used to test the hypotheses H1 and H3 relating to the cardholding demand.

The second dependent variable used to test hypotheses H2 and H4 is the card usage dummy, which takes the value of 1 if the cardholder uses the card as a payment instrument or 0 if he/she pays for goods and services in cash. The data for this dependent variable is also available directly from the survey because the questionnaire asked those respondents, who owned at least one payment card, whether they use their payment cards for purchases of goods and services. Since only those individuals who possess at least one payment card were asked the question, the data on potential card users, who do not own a payment card yet is not available. In order to solve this problem of potential selection bias, the usage dummy variable is estimated as a second step after the selection equation.

Independent variables

Explanatory variables

There are two key categories of the explanatory variables in the models: direct and indirect network effects. In order to measure the network effects we adapt the measures developed in Bounie et al. (2014, 2017), who use the survey data on the French (2014) and European (2017) cardholders and merchants. Their measures of network externalities included the average value of purchases at particular merchant industry and the estimates of the probability that the purchase will be paid for by card given a particular merchant type and transaction value. These measures, however, do not separate the direct and indirect network effects. Besides, they depend on a number of assumptions and calculations performed by authors on proprietary central bank data (Bounie et al., 2014, 2017). The separation of effects was not possible because their surveys of merchants and cardholders were conducted in different years.

Sample used in this study allows mitigating the potential problems of not separated network effects and possibly unrealistic assumptions necessary for calculations. Due to the fact that the individuals and merchants surveys were conducted in the same time period and geographic regions the adapted measures of the previous studies are based on actual average individuals and merchants payment activity in the region. Geographic regions include eight federal districts and thirty three regions. Direct network effect is measured in four possible variations. It could be either the regional average holding of cards or the federal region average holding of cards. Both are calculated as the average share of cardholders in survey sample in a particular region. The latter measure is preferable because the sample was constructed in such way to represent the federal regions. Data on regions may, sometimes, be over- or underestimated due to the absence of quotas at regional level. However, regional variables are used for robustness checks. At the same time, direct network externalities can be measured as either the regional average usage of cards or federal region average usage of cards. Unlike holding of cards, the usage of cards is observed by other cardholders, which may better reflect some of the theoretical mechanisms outlined in the previous sections (e.g., regarding the psychological factors).

Although in theory the effect of the direct network effects may be subject to reverse causality issue because it is calculated as an average occurrence of dependent variable in the sample, this is not the case in the data. Individual decision to hold or use a card is unlikely to affect aggregate outcomes because of the size of the industry. In each of the 8 federal regions there are at least 70 individuals with most of the regions containing more than 100 individuals (except eastern and southern federal regions). Central federal region contains more than 400 individuals. Therefore, individuals cannot affect aggregate outcomes. There are at least 30 people sampled in each of the regions with some regions having more than 100 individuals. Similarly, the aggregate outcomes are unlikely to be affected by individual decision at either regional or federal region levels.

Indirect network effect are based on the sample of 800 traditional (offline) merchants surveyed in the same time period. The nation wide survey included quotas for merchant types and federal regions to ensure sample representatives for Russian merchants market. These network externalities have two possible ways of measurement. The first one is regional average card acceptance rate by merchants. The second one is federal region average card acceptance rate by merchants. Again, the latter is preferred as the data was sampled to be representative at federal region level, while the former is used for the robustness checks.

Control variables

In order to isolate the effect of network effects from the potential effects of other variables that have been found to influence the payment behavior of the individuals we introduce a number of control variables. The key control variables identified in the

previous studies include socio-demographic characteristics of an individual, his education and income levels, travel frequency and the details of a contract with an issuers (Arango-Arango et al., 2018; Bagnall et al, 2014; Bounie & Francois, 2006; Bounie et al., 2016; Gresvik, 2008; Humphrey et al., 1996). The set of controls chosen for the models follow Krivosheya and Korolev (2016), who use the same data sample in order to estimate the effect of individual's benefits level on his/her payment frequency. In a number of unreported robustness checks we also add the regional level characteristics. Although the main results concerning the effect of the network externalities do not change, these are not included in the main analysis because of significant sample reductions due to limited availability of regional level data on relevant characteristics such as the share of grey economy and the intensity of tax evasion practices. The first set of control variables indicate the respondent's age. This data is available directly from the survey. We follow Krivosheya and Korolev (2016), who use age group dummies instead of direct age variable. Previous literature have found that people of older age are less active at the retail payments market, however, the relationship is non-linear because young people are less often involved in the workforce and, hence, do not always have enough funds to maintain card balances by themselves (Arango-Arango et al., 2018; Gresvik, 2008). Age group dummies will reflect such non-linear relationship. Dummies are included for 5 separate groups: 18-24 years old, 25-34 years old, 35-44 years old, 55-64 years old, 65+ years old. 45-54 years old is chosen as a reference category to mitigate perfect multicollinearity.

Another factor affecting the probability to hold and use payment cards is education. Education might reflect the level of financial literacy of a respondent, which links to the level of information an individual processes about the retail payments (Bagnall et al., 2014; Bounie & Francois, 2006; Bounie et al., 2016; Gresvik, 2008). Education is evaluated by beginning professional, middle professional and higher professional dummies, while school is set as a reference category.

Social & demographic measures include married status dummy, children dummy, advanced PC user dummy. Marital status and the number of children can affect the probability to hold and use payment card because of improved family financial management provided by basic banking services related to the payment cards account (e.g., SMS informing about balances) (Bagnall et al., 2014; Bounie et al., 2016; Humphrey et al., 1996). Besides, children and partners can have several payment instruments issued to one account balance, which improves the transfer and uses of income across family members (Bagnall et al., 2014; Bounie et al., 2016; Krivosheya & Korolev, 2016). The level of proficiency with the technology links to the person's ability to conduct cashless payments using basic software and hardware (e.g., digital payments, POS terminals) (Bounie & Francois, 2006; Krivosheya & Korolev, 2016). Technology adoption is proxied by the self-assessment of the level of proficiency with the PC provided by an individual during the survey.

The level of income reflects the ability of an individual to cover fees and expenses associated with payment card issuance and usage (Bagnall et al., 2014; Bounie &

Francois, 2006; Krivosheya & Korolev, 2016). The data on income level of an individual was collected during a survey using the standard sociological FOM (public opinion fund) guidelines regarding the income-related questions. Income level is determined by low income and high income dummies with middle income as a reference category. Threshold levels are determined based on Krivosheya and Korolev (2016).

The cost of cash increases outside of the domestic region because of the forex risks and additional search and transaction costs related to the currency exchange (Arango-Arango et al., 2018; Bagnall et al., 2014; Gresvik, 2008). This argument is especially important for foreign travels. Besides, individuals tend to issue cashless payment instruments for the uses outside home region more often because of the ability to pay larger sums of money than they brought with themselves in cash (Bounie & Francois, 2006; Gresvik, 2008; Krivosheya & Korolev, 2016; Wang, 2008). In fact, the use in travels is one of the top reasons for issuing a card in the sample. Travel frequency is controlled in the holding model and is excluded from the usage model in order to allow for the differences necessary for the model estimation. Some robustness checks are performed with including travel frequency and excluding other control variables groups. The results stay the same. Travel frequency is evaluated using three distinct dummies: frequent travels within Russia dummy, frequent travels within the neighboring foreign countries dummy and frequent travels around the world dummy. The reference category is no traveling at all.

Finally, the characteristics relating to the payment behavior and the contract with an issuer are controlled for in the usage (second stage) model. This vector of controls consists of three dummies: participation in the loyalty program, credit card and the absence of fees for a payment card dummy. Loyalty programs provide additional motivation for using payment cards in order to be reimbursed in bonuses or cashback (Carbó-Valverde & Liñares-Zegarra, 2011; Ching & Hayashi, 2010; Krivosheya & Korolev, 2016). Withdrawals on credit cards are charged additional fees, which make it harder to use cash for a credit card holder (Krivosheya & Korolev, 2016; Rochet & Wright, 2010; Wang, 2008). In case there are no fees paid by an individual, he or she may associate payment card with a costless instrument and, hence, will not be psychologically biased to use a card more often in order to cover the issuance costs (Bagnall et al., 2014; Bounie & Francois, 2006; Krivosheya & Korolev, 2016).

Statistic and econometric methods

In order to mitigate the potential selection and survivorship biases resulting from the fact that the data on usage is available only in case an individual is already a cardholder we need to treat the second model as dependent on the first one. The first (holding) model can, however, be used independently of the usage model. Such dependence of the usage model is possible using the two-stage Heckman selection model. Following Schuh and Stavins (2010) and Krivosheya and Korolev (2016), we use the probit model to estimate cardholding probability and, then, the two-stage

Heckman selection model to estimate the card usage probability. The results of probit model estimation for cardholding probability are also used as a selection equation in card usage probability modeling.

Probit model addresses several issues appearing in OLS (linear probability model) regressions. Firstly, it solves the unboundedness problem which means that predicted probability does not take values out of the [0,1] range. Secondly, probit allows for changing marginal effect of factors across sample. However, probit has some disadvantages as well. For example, probit estimates are inconsistent unless the error term is normal. Moreover, it is more computationally difficult.

The main strength of two-stage Heckman is that it allows to correct for selection bias, which is common in empirical analyses. In the first stage, the probit model estimates the probability that a person has at least one card. The second stage estimates the probability that a person who has at least one card uses it to pay for goods and services. It uses the inverse Mills ratio in order to control for the selection bias. Krivosheya and Korolev (2016), who use the same dataset as the study suggest that the Heckman two stage model outperforms the alternatives, when used to estimate the Russian individual's payment behavior. There are also some drawbacks that need to be accounted for during the second stage of the modeling. These can include the potential multicollinearity of explanatory variable in the second stage which leads to inconsistent estimates. To solve this problem, we need to add at least one extra predictor in the first step. In the usage model we exclude the travel related control variables and add payment characteristics vector instead. We use robust standard errors in all of the models to account for potential heteroscedasticity as well as other error related issues.

In order to address economic significance of the network effects in the both models we also calculate the marginal effects at the average values of all the characteristics included into the regression.

Table 1 provides descriptive statistics and cross-correlations of the variables used in the main analysis. Most of the correlation coefficients sign at the absence of multicollinearity as the correlations are less than 50%, except for the relationship between federal and regional variables. These variables are not used in most of the regression specifications simultaneously. Some specifications towards the end of the study include these variables simultaneously using the aggregated factors obtained from the results of the principal component analysis (PCA) to mitigate the multicollinearity problem. These factors are provided in table 1 as well.

Table 1

		Mean	S.D.	Min	Max
-1	18-24 y.o.	0.16	0.37	0.00	1.00
-2	25-34 y.o.	0.21	0.41	0.00	1.00
-3	35-44 y.o.	0.17	0.37	0.00	1.00
-4	55-64 y.o.	0.16	0.37	0.00	1.00
-5	65+ y.o.	0.13	0.34	0.00	1.00
-6	beg_prof	0.09	0.29	0.00	1.00
-7	mid_prof	0.32	0.46	0.00	1.00
-8	high_prof	0.34	0.48	0.00	1.00
-9	Married	0.60	0.49	0.00	1.00
-10	Have children	0.38	0.49	0.00	1.00
-11	Advanced PC User	0.71	0.45	0.00	1.00
-12	Low income	0.11	0.31	0.00	1.00
-13	High income	0.31	0.46	0.00	1.00
-14	Frequent travels within Russia	0.05	0.22	0.00	1.00
-15	Frequent travels within the neighboring foreign countries	0.02	0.13	0.00	1.00
-16	Frequent travels around the world	0.03	0.16	0.00	1.00
-17	Participates in the loyalty program	0.16	0.36	0.00	1.00
-18	Credit card	0.04	0.20	0.00	1.00
-19	No fees for card	0.30	0.46	0.00	1.00
-20	Regional Component: Usage	0.00	1.20	-3.09	3.29
-21	Federal Region Component: Usage	0.00	1.26	-3.44	3.29
-22	Federal Region Average Holding of Cards	0.73	0.06	0.49	0.79
-23	Federal Region Average Usage of Cards	0.55	0.06	0.46	0.72
-24	Regional Average Holding of Cards	0.73	0.11	0.42	1.00
-25	Regional Average Usage of Cards	0.55	0.13	0.05	0.88
-26	Federal Region Average Acceptance Rate	0.50	0.06	0.39	0.63
-27	Regional Average Acceptance Rate	0.52	0.09	0.20	0.70

4 Results and discussion

Unilateral tests

Before conducting the complete multilateral analysis using the method set-up in the previous section we present the results of unilateral analysis. In order to do so we start with the comparison of means between the sub samples of card holding and non-holding individuals. The t-statistic for the equality of means of federal region average cardholding is -5.18, which allows rejecting the hypothesis of mean equality at any reasonable significance level. Similarly, the t-statistic for the equality of means of federal region card usage is -3.13. Regional level definition of direct network externalities produces the same results. Thus, unilateral tests show that the individuals holding payment cards are, on average, exposed to larger indirect network effects. This supports hypothesis H1.

Similarly, for the using and non-using cardholders sub-samples the t-statistic is -2.86 for the average federal region cardholding rate and -4.73 for the average federal region card usage rate. Hence, H3 is also not rejected yet. Federal region acceptance level is also different for the subsamples by holding and usage of payment cards. Respective t-statistics are -3.47 and -3.67, which supports H2 and H4 hypotheses. Therefore, we can conclude that the network effects do affect the probability of credit card holding and usage. This allows me to move to the multirateral tests in order to explain that the association found is indeed present and is not the result of omitted variable bias or spurious correlations.

Multirateral tests

Cardholding probability

We begin by analyzing the determinants of the cardholding probability using the probit estimation method for the first model developed in the previous section. Table 2 presents the results. These results address hypotheses H1 and H3 regarding the effect of network externalities on cardholding probability.

Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Baseline Model	Direct NE: Regional Holding	Direct NE: Federal Regional Holding	Direct NE: Regional Usage	Direct NE: Federal Regional Usage	Indirect NE: Regional Acceptance	Direct NE: Federal Regional Acceptance
NETWORK EFFECTS							
Regional Average Holding of Cards		3.227***					
		(0.359)					

Federal Region Average Holding of Cards			2.687***				
			(0.612)				
Regional Average Usage of Cards				1.777***			
				(0.311)			
Federal Region Average Usage of Cards					1.555**		
					(0.692)		
Regional Average Acceptance Rate						1.103**	
						(0.524)	
Federal Region Average Acceptance Rate							2.000**
							(0.782)
Regional Component: Usage							
Federal Region Component: Usage							
AGE							
18-24 y.o.	-0.0813	-0.0998	-0.0706	-0.0816	-0.0767	-0.214	-0.218
	(0.142)	(0.147)	(0.143)	(0.146)	(0.143)	(0.173)	(0.173)
25-34 y.o.	0.137	0.111	0.151	0.125	0.140	0.155	0.153
	(0.135)	(0.140)	(0.135)	(0.137)	(0.135)	(0.161)	(0.161)
35-44 y.o.	0.110	0.0810	0.105	0.0924	0.120	0.121	0.131
	(0.139)	(0.143)	(0.140)	(0.141)	(0.140)	(0.164)	(0.165)
55-64 y.o.	0.0429	-0.0369	0.0232	0.0264	0.0384	0.149	0.143
	(0.130)	(0.132)	(0.130)	(0.131)	(0.130)	(0.160)	(0.161)
65+ y.o.	-0.646***	-0.655***	-0.653***	-0.634***	-0.632***	-0.501***	-0.490***
	(0.135)	(0.138)	(0.136)	(0.137)	(0.135)	(0.172)	(0.172)
EDUCATION							
Beginning Professional	0.293**	0.273**	0.289**	0.306**	0.308**	0.376**	0.350**
	(0.135)	(0.138)	(0.135)	(0.136)	(0.135)	(0.163)	(0.162)
Middle Professional	0.452***	0.391***	0.436***	0.435***	0.442***	0.485***	0.472***
	(0.0994)	(0.103)	(0.100)	(0.101)	(0.0999)	(0.126)	(0.127)
Higher Professional	0.465***	0.481***	0.472***	0.494***	0.473***	0.503***	0.503***
	(0.102)	(0.106)	(0.103)	(0.104)	(0.102)	(0.126)	(0.126)
SOCIAL & DEMOGRAPHIC CHARACTERISTICS							
Married	0.0706	0.0805	0.0892	0.0655	0.0676	-0.0715	-0.0755
	(0.0819)	(0.0840)	(0.0827)	(0.0834)	(0.0825)	(0.101)	(0.101)
Have children	0.0712	0.0894	0.0489	0.112	0.0594	-0.0353	-0.0574
	(0.0885)	(0.0910)	(0.0896)	(0.0898)	(0.0889)	(0.103)	(0.104)
Advanced PC User	0.589***	0.547***	0.560***	0.561***	0.580***	0.741***	0.741***

	(0.101)	(0.103)	(0.102)	(0.103)	(0.101)	(0.128)	(0.128)
INCOME LEVEL							
Low income	-0.191	-0.204*	-0.217*	-0.218*	-0.220*	-0.295*	-0.291*
	(0.118)	(0.119)	(0.119)	(0.119)	(0.118)	(0.157)	(0.156)
High income	0.0589	0.0904	0.0789	0.0807	0.0611	0.0863	0.101
	(0.0890)	(0.0920)	(0.0893)	(0.0899)	(0.0889)	(0.104)	(0.105)
TRAVEL FREQUENCY							
Frequent travels within Russia	0.222	0.253	0.214	0.240	0.234	0.142	0.160
	(0.208)	(0.216)	(0.209)	(0.208)	(0.206)	(0.220)	(0.220)
Frequent travels within the neighboring foreign countries	-0.159	-0.119	-0.142	-0.115	-0.158	0.243	0.218
	(0.341)	(0.337)	(0.339)	(0.338)	(0.341)	(0.404)	(0.403)
Frequent travels around the world	-0.350	-0.408	-0.359	-0.336	-0.333	-0.661**	-0.617**
	(0.271)	(0.263)	(0.267)	(0.266)	(0.268)	(0.304)	(0.304)
Constant	-0.0670	-2.345***	-2.014***	-1.025***	-0.910**	-0.736**	-1.143***
	(0.131)	(0.290)	(0.460)	(0.219)	(0.398)	(0.318)	(0.416)
Observations	1,500	1,500	1,500	1,500	1,500	1,019	1,019
Pseudo R2	0.145	0.191	0.157	0.165	0.149	0.149	0.150

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

To begin with, the initial specification (1) is the baseline model with the factors outlined in previous studies (e.g., Krivosheya & Korolev, 2018). It includes only control variables identified in the previous section. Network externalities are not yet included. According to the Panel A of Table 2 significant variables and their signs are the same as expected and correspond to the previous studies (Krivosheya, Korolev 2016). In particular, the probability to hold payment cards decreases with age (dummy variable for 65+ years old is significant and exhibits negative correlation with cardholding probability). Also, education increases cardholding probability significantly. All of the dummy variables indicate that the more educated individuals are more likely to hold cards. Proficiency with technology positively affects cardholding probability as expected. All of the other controls are not significant, however, they cannot be excluded from the model since their exclusion may lead to the omitted controls problem and result in inconsistent estimates. We can further use these variables as controls and collected data to analyze the relationship between dependent and explanatory variables.

Panel A of Table 2 presents the results for the effect of the direct and indirect network effects on cardholding probability. Predictive power of the models is similar to the previous studies in this area (e.g., Arango-Arango et al., 2018; Krivosheya & Korolev,

2018). .Models (2)-(5) add different measures of the direct network effect to the baseline model. In model (2) the direct network effect is measured as the regional average holding of cards. The positive effect is significant at 1% significance level. In model (3) we change the direct network effects measure for the federal region average holding of card. The result stays similar to model (2). Model (4) introduces regional average usage of card, which is observable to the cardholders in region and, hence, may introduce distinct mechanisms outlined in the theoretical framework section. The result is, again, significant at 1% significance level and the effect is positive. Finally, model (5) uses federal region average usage of card. As in all of these cases the direct network externality effect is positive and significant. Other controls also exhibit the same significance and direction of the effects as in baseline model. These results support hypothesis H1 stated in the theoretical framework meaning that the positive mechanisms on the fixed net benefits are indeed present at Russian retail payments market. In order to assess economic significance of results we also calculate the marginal returns of the presented models. When federal region usage is used as direct network externalities proxy, one standard deviation increase in this measure increases cardholding probability by 2.9 percentage points.

Having analyzed the direct network effect separately, we do the same with the indirect network effects in models (6) & (7). We add two measures of the indirect network effects to the baseline model. Again, the indirect network effect is measured as either the regional average acceptance rate or the federal region average acceptance rate by merchants. Similarly to direct effect, the indirect network effect is always positively significant and increases the demand for cardholding. Model (6) shows that at 5% significance level regional average acceptance rate increases the probability of cardholding. Similarly, Model (7) introduces the main measure of indirect network effects at federal region level and concludes the same: at 5% significance level there is positive association between cardholding probability and indirect network effects. So, the hypothesis H3 that probability of cardholding increases with higher share of accepting merchants is also not rejected. Merchant acceptance induces higher net benefits for individuals, which leads to higher cardholding probability.

From the economics point of view, one standard deviation increase in the federal region average acceptance rate increases the probability of cardholding by 3.79 percentage points, holding all other parameters fixed. Similarly, having beginning professional education increases the probability of cardholding by 8.33 percentage points in comparison with only school. The result is economically significant.

In order to compare the results with the previous studies that did not separate the effects of direct and indirect network effects we add these two network externalities simultaneously in panel B. In these models we separately aggregate the network effects on regional level and federal region level . First, we add the regional average holding of cards and regional average acceptance rate in model (8) to investigate the simultaneous effect of both network externalities. In this case indirect network externality becomes insignificant. When tested in model (9), same result persists on

the federal region level. Potential explanation may be linked to the multicollinearity problem between direct and indirect network effects at the same level of aggregation (correlation coefficients between acceptance and holding (usage) are 0.69 (0.82) at federal region level). In order to mitigate the multicollinearity problem and get valid results we use principal component analysis (PCA) based on (federal) regional usage and (federal) regional acceptance levels to construct an aggregate factor. The results of model estimation with such factors are presented in models (10) and (11). Both federal and regional components are significant at 5% significance level.

Simultaneously network effects account for smaller share of probability than the simple sum of two separate contributions. This happens because some of the underlying mechanisms coincide for both externality types. One standard deviation increase in aggregate factor at federal region level results in 3.13 percentage points increase in cardholding probability. The result is significant economically as well as statistically.

Overall, according to the results of the probit model estimation hypotheses H1 and H3 about cardholding probability are confirmed. An individual is indeed more likely to hold the card if the network effects are greater. Therefore, the mechanisms outlined in the theoretical framework regarding the effects of the network externalities on net fixed benefits hold in case of Russian retail payments market. The results are robust to the changes in measures from federal region to regional level.

Card usage probability

To test the remaining two hypotheses regarding the card usage probability we present the results of the analysis using the two-step Heckman model. Results are outlined in table 3. Selection equations presented in models (2) and (7) are equivalent to the results of baseline model estimation in previous subsection and represent the first step of the Heckman two-step procedure. Mills ratio is presented on the line lambda. As in Krivosheya and Korolev (2018) the results suggest that using the Heckman two-stage model provides better model fit than the separate probit models because of the potential selection (or survivorship) bias as a result of the fact that the data on card usage is available only on cardholders.

Table 3

	(1)	(2)	(4)	(5)	(7)	(8)	(10)
VARIABLES	Baseline Model	Baseline Model	Direct NE: Regional Holding	Direct NE: Regional Holding	Direct NE: Federal Regional Holding	Direct NE: Federal Regional Holding	Direct NE: Regional Usage
NETWORK EFFECTS							

Regional Average Holding of Cards			-0.103				
			(0.0969)				
Federal Region Average Holding of Cards					-0.176		
					(0.206)		
Regional Average Usage of Cards							0.522***
							(0.0838)
Federal Region Average Usage of Cards							
Regional Average Acceptance Rate							
Federal Region Average Acceptance Rate							
Regional Component: Usage							
Federal Region Component: Usage							
AGE							
18-24 y.o.	0.0779*	-0.0813	0.0774*	-0.0813	0.0768*	-0.0813	0.0785*
	(0.0423)	(0.144)	(0.0418)	(0.144)	(0.0420)	(0.144)	(0.0412)
25-34 y.o.	0.0723*	0.137	0.0754*	0.137	0.0731*	0.137	0.0686*
	(0.0392)	(0.134)	(0.0390)	(0.134)	(0.0390)	(0.134)	(0.0383)
35-44 y.o.	0.0199	0.110	0.0215	0.110	0.0211	0.110	0.0186
	(0.0397)	(0.136)	(0.0393)	(0.136)	(0.0394)	(0.136)	(0.0387)
55-64 y.o.	-0.0724*	0.0429	-0.0683*	0.0429	-0.0706*	0.0429	-0.0804**
	(0.0393)	(0.129)	(0.0391)	(0.129)	(0.0391)	(0.129)	(0.0384)
65+ y.o.	-0.154	-0.646***	-0.164	-0.646***	-0.162	-0.646***	-0.161
	(0.124)	(0.138)	(0.124)	(0.138)	(0.124)	(0.138)	(0.122)
EDUCATION							
Beginning Professional	-0.0873	0.293**	-0.0850	0.293**	-0.0840	0.293**	-0.0682
	(0.0643)	(0.138)	(0.0639)	(0.138)	(0.0641)	(0.138)	(0.0630)
Middle Professional	-0.0188	0.452***	-0.0123	0.452***	-0.0149	0.452***	-0.0124
	(0.0717)	(0.0989)	(0.0717)	(0.0989)	(0.0717)	(0.0989)	(0.0703)
Higher Professional	0.0126	0.465***	0.0164	0.465***	0.0159	0.465***	0.0315
	(0.0721)	(0.102)	(0.0719)	(0.102)	(0.0720)	(0.102)	(0.0707)
SOCIAL & DEMOGRAPHIC CHARACTERISTICS							
Married	0.000124	0.0706	0.000491	0.0706	0.000278	0.0706	-0.00534
	(0.0262)	(0.0828)	(0.0259)	(0.0828)	(0.0260)	(0.0828)	(0.0256)
Have children	0.00970	0.0712	0.00951	0.0712	0.0104	0.0712	0.0170
	(0.0260)	(0.0857)	(0.0257)	(0.0857)	(0.0258)	(0.0857)	(0.0254)
Advanced PC User	0.0700	0.589***	0.0760	0.589***	0.0752	0.589***	0.0798
	(0.0937)	(0.102)	(0.0935)	(0.102)	(0.0937)	(0.102)	(0.0919)

INCOME LEVEL							
Low income	-0.00695	-0.191	-0.00926	-0.191	-0.00808	-0.191	-0.0153
	(0.0514)	(0.119)	(0.0511)	(0.119)	(0.0512)	(0.119)	(0.0503)
High income	0.0647**	0.0589	0.0655***	0.0589	0.0657***	0.0589	0.0654***
	(0.0252)	(0.0893)	(0.0250)	(0.0893)	(0.0251)	(0.0893)	(0.0246)
PAYMENT BEHAVIOR DETAILS							
Participates in the loyalty program	0.192***		0.190***		0.189***		0.179***
	(0.0267)		(0.0267)		(0.0269)		(0.0263)
Credit card	0.147***		0.147***		0.145***		0.138***
	(0.0461)		(0.0460)		(0.0461)		(0.0453)
No fees for card	0.352***		0.355***		0.353***		0.325***
	(0.0215)		(0.0216)		(0.0215)		(0.0215)
TRAVEL FREQUENCY							
Frequent travels within Russia		0.222		0.222		0.222	
		(0.205)		(0.205)		(0.205)	
Frequent travels within the neighboring foreign countries		-0.159		-0.159		-0.159	
		(0.355)		(0.355)		(0.355)	
Frequent travels around the world		-0.350		-0.350		-0.350	
		(0.268)		(0.268)		(0.268)	
Constant	0.560**	-0.0670	0.618**	-0.0670	0.676**	-0.0670	0.257
	(0.243)	(0.134)	(0.248)	(0.134)	(0.278)	(0.134)	(0.243)
Lambda		-0.224				-0.209	
		(0.301)				(0.301)	
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500
P-value of comparison test	0	0	0	0	0	0	0

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model (1) provides the results of the baseline model estimation without network effects. with new a baseline model. Column (2) is the selection equation for all of the models containing 1500 observations (models (1)-(6)). Most of the controls remain as in probit models but we also include payment behavior details instead of travel frequency. The significance and signs of the controls are the same as in previous studies, so the data and control variables allow me to analyze the association between dependent and explanatory variables. In particular, all of the payment characteristics details (i.e., loyalty program participation, absence of fees and credit card) are significant at 1% significance level and increase the probability of card

usage. Also, high income dummy remains significant for the card usage probability. The hypothesis on non-linear association with the age groups is also confirmed as in Arango-Arango et al. (2018) and Krivosheya & Korolev (2018).

As before we begin by adding direct network effects into the baseline model and obtain first four specifications presented in the Panel A of Table 3. Direct network effects is evaluated by the same average holding and usage levels as before at both regional and federal region levels. Models (3) and (4) suggest that the average holding levels are not significant for the card usage probability. As outlined in the theoretical framework, some of the mechanisms behind the influence of the average cardholding levels are not strong enough for the variable net benefits as the cardholding decisions are rarely evident to the individuals and more often affect only the behavior of issuing banks.

In models (5) and (6) we add the average regional and federal region usage levels instead of holding levels. The effect of direct network effects becomes positive and significant at any reasonable significance level. From the economic point of view, a standard deviation increase in the average federal region usage of cards results in the 3.34 percentage point increase in card usage probability by each particular merchant. In comparison, being a high income instead of middle income individual increases card usage probability by 2.9 percentage points, which allows concluding that the direct network effects are significant both economically and statistically. Therefore, hypothesis H2 is not rejected and the direct network effects increase the probability of the card usage even when controlled for other individual characteristics and potential selection bias.

In order to test hypothesis H4 we add the indirect network effects in models (8) and (9). Some reduction in the number of observations happens due to the availability of data on merchants acceptance. In model (8) regional level average acceptance rate is used as a proxy for the indirect network effects, while federal region average acceptance rate is presented in model (9). In contrast to the direct network externalities results, the indirect network effects are always positive and significant for the card usage probability. It is important to note that the federal region average acceptance level is significant only at 10% significance level. This partial decrease in the results significance is explained by the fact that there are fewer mechanisms underlying the effect of indirect network effects on the variable net cardholders' benefits and, hence, the effect on card usage probability might be smaller compared to the cardholding probability. This is indeed evident from the economic point of view, because, as revealed by the marginal effects, one standard deviation increase in federal region acceptance level increases the probability of card usage by 2.41 percentage points. This effect was larger for the cardholding demand. However, since the effect is still significant, the hypothesis H4 that the probability of card usage indeed increases with the higher share of accepting merchants is also not rejected and we may conclude that the theoretical mechanisms identified in the previous sections of

this research indeed persist in case of Russian cardholders. This result persists when we use regional average card acceptance levels instead of federal region level.

Finally, we repeat the final step of probit analysis and add both direct and indirect network effects into the baseline model. Models (10) – (13) of panel B present the results. As in probit, only PCA analysis provides us two valid specifications which show that combined network effects are positively associated with the card usage probability and significant at 1% significance level. Once the network effects are included separately, the effect of both (in model (10)) and indirect (in model (11)) disappears. This is, again, explained by high correlation between the explanatory variables and, therefore, support the robustness of the presented results regarding hypotheses H2 and H4. From the economic point of view, a standard deviation in federal region component increases cashless payment usage probability by 3.96 percentage points.

Having analyzed the results of both models estimations, we can conclude that both direct and indirect effects are important for card holding and card usage as was stated in the theoretical framework. All of the hypotheses presented in this study are not rejected. Despite the high role of cash and yet fragile payment preferences of the Russian individuals noted in previous studies this research was able to show that the effects of indirect and direct network externalities are present in reality. Therefore, net cardholders' benefits are in fact affected by the level of the retail payments market development at regional and federal region levels. The results are robust to changes in measures. The effect of aggregated network effects persists in case of Russian markets in line with the articles that analyzed the network effects at other geographies. However, separation of the network externalities into direct and indirect allows capturing the differences between the underlying mechanisms at play, which were provided only in theory before.

5 Conclusion

This research empirically evaluates the effect of direct and indirect network externalities for cardholding and card usage probabilities in Russia. The survey on which this research is based was conducted to form a representative sample of 1500 individuals from all Russian regions. This article finds significant and robust evidence in favor of positive association between the degree of both types of network externalities and the individuals' activity at the Russian retail payment market. Indirect network effects, associated with the higher acceptance rate at the merchants' side of the market increase the probability of cardholding and card usage. Similarly, direct network effects that result from the increased activity of individuals (in terms of cardholding and card usage) rise the probability that each cardholder holds the payment cards and pays by it. Besides, the results are significant from economical point of view. Direct externalities have similar effect: one standard deviation increase in the average federal region usage rate of payment cards increases the probability of card holding by 2.9 percentage points and using by 3.34 percentage points. One standard deviation increase in the average federal region card acceptance by

merchants increases probability of card holding by 3.79 percentage points and card usage by 2.41 percentage points. One standard deviation increase in the combined factor reflecting both network externalities at the federal region level increases the probability of card holding by 3.13 percentage points and using by 3.96 percentage points. These results are significant in comparison to the effects of other control variables.

This research aims to contribute to the rising literature on the determinants of cashless payments instrument holding and usage (Arango-Arango, Bouhdaoui, Bounie, Eschelbach, & Hernandez, 2018; Bagnall et al., 2014; Bounie & Francois, 2006; Bounie, François, & Hove, 2016; Carbó-Valverde & Liñares-Zegarra, 2011; Gresvik, 2008). Most of the studies do not investigate the presence of network externalities for the customers empirically and those that do fail to distinguish between direct and indirect network externalities. Besides, none of the articles outline the network externalities on Russian retail payments market. Also, none of the studies provide empirical investigation of the effects of network externalities on the cardholding probability and study the effect only on the usage. This study fills these gaps by analyzing empirically the effect of network externalities at Russian retail payments market in the context of cardholding and card usage probabilities of an individual.

Only Krivosheya and Korolev (2016) study the characteristics of the cardholding and card usage of Russian individuals. Their study, however, focuses on the evaluation of the aggregated cardholders' benefits resulting from the participation in the retail payments market compared to using cash based instruments. It does not, therefore, provide any investigation into the effect of the network externalities on individuals' probability to hold and use cards. This research is complementary to Krivosheya and Korolev (2018) and extends the findings by providing empirical estimates of the effect of network externalities.

The results of the study are important not only from theoretical but also from practical point of view. Financial structures implement different stimulating programs aimed at cardholding and usage behavior stimulation. However, the degree of potential influence depends on the magnitude of the network effects which can not be explicitly changed by pure public or private sector intervention. Accounting for this, the real degree of influence could be measured and forecasted by Central Bank of Russia, commercial banks and payment systems.

There are some limitations in this study that provide the directions for further research. First of all, we analyzed network effects only in Russia but this effect could vary from country to country. In developing countries there could be no network effects at all due to the early stage of market development. Other countries could be analyzed both separately and together to investigate the effect of cross-border payments and the presence of network externalities among groups with smaller degree of communication. Secondly, the data was collected from the cities with at least 500 thousand inhabitants but there are also smaller cities, where the degree of network externalities may be smaller. Although this restriction does not threaten the

representativeness of the data, it is worth considering them either separately or as a part of similar national study. Thirdly, the latest available data was collected in 2013-2014. Despite the fact that the direction and presence of network externalities should not differ much, the association between network effects and demand for card holding and acceptance may intensify due to the evolution of payment technologies and innovation. Future studies could test this hypothesis empirically.

6 References

Ali, R., Barrdear, J., Clews, R., & Southgate, J. (2014). Innovations in Payment Technologies and the Emergence of Digital Currencies. Rochester, NY: Social Science Research Network.

Arango, C., & Taylor, V. (2008). Merchant Acceptance, Costs, and Perceptions of Retail Payments: A Canadian Survey (Discussion Paper No. 08–12). Bank of Canada.

Arango, C., & Taylor, V. (2008). Merchants' Costs of Accepting Means of Payment: Is Cash the Least Costly? Bank of Canada Review, 2008–2009(Winter), 17–25.

Arango-Arango, C. A., Bouhdaoui, Y., Bounie, D., Eschelbach, M., & Hernandez, L. (2018). Cash remains top-of-wallet! International evidence from payment diaries. Economic Modelling, 69, 38–48.

Asokan, N., Janson, P., Steiner, M., & Waidner, M. (2000). State of the art in electronic payment systems. B M. V. Zelkowits, Advances in Computers (53, 425–449). Elsevier.

Au, Y. A., & Kauffman, R. J. (2008). The economics of mobile payments: Understanding stakeholder issues for an emerging financial technology application. Electronic Commerce Research and Applications.

Bagnall, J., Bounie, D., Huynh, K. P., Kosse, A., Schmidt, T., Schuh, S. D., & Stix, H. (2014). Consumer Cash Usage: A Cross-Country Comparison with Payment Diary Survey Data. Rochester, NY: Social Science Research Network.

Baxter, W. F. (1983). Bank Interchange of Transactional Paper: Legal and Economic Perspectives. The Journal of Law & Economics, 26(3), 541–588.

Bayero, M. A. (2015). Effects of Cashless Economy Policy on Financial Inclusion in Nigeria: An Exploratory Study. Procedia - Social and Behavioral Sciences, 172, 49–56.

Bedre-Defolie, O., & Calvano, E. (2013). Pricing Payment Cards. American Economic Journal: Microeconomics, 5(3), 206–231.

Bolt, W., & Chakravorti, S. (2008). Economics of payment cards: a status report. Economic Perspectives, Q IV, 15–27.

Bolton, R. N., Kannan, P. K., & Bramlett, M. D. (2000). Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value. Journal of the Academy of Marketing Science, 28(1), 95–108.

Borzekowski, R., Elizabeth, K. K., & Shaista, A. (2008). Consumers' Use of Debit Cards: Patterns, Preferences, and Price Response. Journal of Money, Credit and Banking, 40(1), 149–172.

Bounie, D., & Francois, A. (2006). Cash, Check or Bank Card? The Effects of Transaction Characteristics on the Use of Payment Instruments. Rochester, NY: Social Science Research Network.

Bounie, D., François, A., & Hove, L. V. (2016). Consumer Payment Preferences, Network Externalities, and Merchant Card Acceptance: An Empirical Investigation. Review of Industrial Organization, 1–34.

Carbó-Valverde, S., & Liñares-Zegarra, J. M. (2011). How effective are rewards programs in promoting payment card usage? Empirical evidence. Journal of Banking & Finance, 35(12), 3275–3291.

Carbo-Valverde, S., & Liñares-Zegarra, J. M. (2012). Payment Card Interchange Fees: Assessing the Effectiveness of Antitrust Investigations and Regulation in Europe. Rochester, NY: Social Science Research Network.

Chernikova, L. I., Faizova, G. R., Egorova, E. N., & Kozhevnikova, N. V. (2015). Functioning and Development of Retail Banking in Russia. Mediterranean Journal of Social Sciences, 6(6 S4), 274.

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

Chizhikova, E. S. (2013). The Current Payment System of the Russian Federation. Middle-East Journal of Scientific Research, 14(2), 244–247.

Darban, M., & Amirkhiz, H. (2015). Herd Behavior in Technology Adoption: The Role of Adopter and Adopted Characteristics. 2015 48th Hawaii International Conference on System Sciences (cc. 3591–3600).

de Kerviler, G., Demoulin, N. T. M., & Zidda, P. (2016). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? Journal of Retailing and Consumer Services, 31, 334–344.

Grauwe, D., Paul, & Rinaldi, L. (2002). A Model of the Card Payment System and the Interchange Fee. Rochester, NY: Social Science Research Network. Извлечено от

Gresvik, O. (2008). Payment habits at point of sale : different methods of calculating use of cards and cash in Norway.

Guthrie, G., & Wright, J. (2007). Competing Payment Schemes*. The Journal of Industrial Economics, 55(1), 37–67.

Hasan, I., Schmiedel, H., & Song, L. (2012). Returns to Retail Banking and Payments. Journal of Financial Services Research, 41(3), 163–195.

Hayashi, F. (2008). Do U.S. Consumers Really Benefit from Payment Card Rewards?

Humphrey, D. B. (2010). Retail payments: New contributions, empirical results, and unanswered questions. Journal of Banking & Finance, 34(8), 1729–1737.

Humphrey, D. B., Pulley, L. B., & Vesala, J. M. (1996). Cash, Paper, and Electronic Payments: A Cross-Country Analysis. Journal of Money, Credit and Banking, 28(4), 914.

Humphrey, D., Willesson, M., Lindblom, T., & Bergendahl, G. (2003). What Does it Cost to Make a Payment? Review of Network Economics, 2(2).

Hunt, R. M. (2003). An Introduction to the Economics of Payment Card Networks. Review of Network Economics, 2(2).

Jonkers, N. (2011). Card Acceptance and Surcharging: the Role of Costs and Competition : Review of Network Economics.

Kadhiwal, S., & Zulfiquar, A. U. S. (2007). Analysis of mobile payment security measures and different standards. Computer Fraud & Security, 2007(6), 12–16.

Kim, C., Tao, W., Shin, N., & Kim, K.-S. (2010). An empirical study of customers' perceptions of security and trust in e-payment systems. Electronic Commerce Research and Applications, 9(1), 84–95.

Krivosheya, E., & Korolev, A. (2016). Benefits of the retail payments card market: Russian cardholders' evidence. Journal of Business Research, 69(11), 5034–5039.

Krivosheya, E., & Korolev, A. (2018). Benefits of the retail payments card market: Evidence from Russian merchants. Journal of Business Research, 88, 466–473.

Krivosheya, E., Korolev, A., & Plaksenkov, E. (2015). Measures for stimulating a cashless economy in Russia. Moscow School of Management SKOLKOVO working paper.

Krivosheya, E., Semerikova, E., Korolev, A. & Tarusova, E. (2017). Cashless economy in Russia 2030: Scenarios for market and industry. Moscow School of Management SKOLKOVO Working Paper.

Krivosheya, E. (2018). Evaluating efficient multilateral interchange fees: evidence from end-user benefits. Moscow School of Management SKOLKOVO Working Paper.

Malaguti, M. C., & Guerrieri, A. (2014). Multilateral Interchange Fees: Competition and regulation in light of recent legislative developments. ECRI Research Report No. 14, 31 January 2014

Manchanda, R. V., & Saqib, N. (2008). Consumers' evaluations of co-branded products: the licensing effect. Journal of Product & Brand Management, 17(2), 73–81.

Mas, I., & Radcliffe, D. (2010). Mobile Payments go Viral: M-PESA in Kenya. Worldbank, CGAP.

Massoth, M., & Bingel, T. (2009). Performance of Different Mobile Payment Service Concepts Compared with a NFC-Based Solution. 2009 Fourth International Conference on Internet and Web Applications and Services (cc. 205–210).

McGinnis, P. C. (2012). Misguided Regulation of Interchange Fees: The Consumer Impact of the Durbin Amendment. Loyola Consumer Law Review, 25, 285.

Meadows, M., & Dibb, S. (1998). Assessing the implementation of market segmentation in retail financial services. International Journal of Service Industry Management, 9(3), 266–285.

Milne, A. (2006). What is in it for us? Network effects and bank payment innovation. Journal of Banking & Finance, 30(6), 1613–1630.

Plaksenkov, E., Korovkin, V., & Krivosheya, E. (2015). Cashless economy in Russia: Tendencies, perspectives, opportunities. Moscow School of Management SKOLKOVO Working Paper.

Roberts, J. A., & Jones, E. (2001). Money Attitudes, Credit Card Use, and Compulsive Buying among American College Students. Journal of Consumer Affairs, 35(2), 213–240.

Rochet, J.-C., & Tirole, J. (2002). Cooperation among Competitors: Some Economics of Payment Card Associations. The RAND Journal of Economics, 33(4), 549–570.

Rochet, J.-C., & Tirole, J. (2003). Platform Competition in Two-sided Markets. Journal of the European Economic Association, 1(4), 990–1029.

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: a progress report. The RAND Journal of Economics, 37(3), 645–667.

Rochet, J.-C., & Wright, J. (2010). Credit card interchange fees. Journal of Banking & Finance, 34(8), 1788–1797.

Rysman, M., & Schuh, S. (2017). New Innovations in Payments. Innovation Policy and the Economy, 17, 27–48.

Shy, O. (2011). A Short Survey of Network Economics. Review of Industrial Organization, 38(2), 119–149.

Slade, E. L., Williams, M. D., & Dwivedi, Y. K. (2013). Mobile payment adoption: Classification and review of the extant literature.

Souvignet, T., Hatin, J., Maqua, F., Tesniere, D., Léger, P., & Hormière, R. (2014). Payment card forensic analysis: From concepts to desktop and mobile analysis tools. Digital Investigation, 11(3), 143–153.

Teo, A.-C., Ooi, K.-B., Yew, K.-T., Tan, G. W.-H., & Hew, T.-S. (2015). The effects of convenience and speed in m-payment. Industrial Management & Data Systems, 115(2), 311–331.

Todd, S., & Lawson, R. (2003). Consumer preferences for payment methods: a segmentation analysis. International Journal of Bank Marketing, 21(2), 72–79.

Wang, Y. (2008). Determinants Affecting Consumer Adoption of Contactless Credit Card: An Empirical Study. CyberPsychology & Behavior, 11(6), 687–689.

Weiner, S., & Wright, J. (2005). Interchange Fees in Various Countries: Developments and Determinants. Review of Network Economics, 4(4), 1–34.

Worthington, S. (1999). Branding and relationships issues in affinity and co-branded credit cards. Journal of Brand Management, 6(3), 188–197.

Wright, J. (2004). The Determinants of Optimal Interchange Fees in Payment Systems. The Journal of Industrial Economics, 52(1), 1–26.