A FEASIBLE APPROACH TO PROJECTING HOUSEHOLD DEMAND FOR THE DIGITAL RUBLE IN RUSSIA

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ABSTRACT

We estimated a model of households' usage of alternative payment instruments (cash and bank cards) using a new dataset from a survey of Russian households. In our modelling set-up, households' preferences are determined by the instruments' perceived attributes and hence their choice regarding payment methods depends on the differences across instruments in these attributes. The results indicate a statistically significant sensitivity of consumer choice to the perceived attributes. We employ the estimated model to evaluate the demand for CBDC depending on its expected design and consumers' perception of it. We discuss several illustrative projections to demonstrate the application of the tool developed. The predicted utilisation of CBDC varies considerably depending on the attributes hypothesised, although under the conservative assumptions, the projected use of CBDC in household transactions is limited.

Keywords: Central Bank Digital Currency, Digital Ruble, payment instruments, ordered probit, banknotes, bank cards, Russia.

JEL classification: E42, E47, E50, E58

Contents

1. INTRODUCTION

In recent years, both advanced and emerging economies have faced a number of trends which may change the monetary landscape in the near future. These include the declining use of cash for payments, the development of fintech and big-tech activities, and the rapid rise of cryptoassets. If left unattended, these trends may dampen the effectiveness of monetary policy and pose threats to financial stability. To meet these challenges, central banks all over the world are considering the creation of a new form of fiat money with digital properties — central bank digital currencies (CBDC). As central bank liabilities, CBDC will combine features of both cash and cashless money.[1]

The Bank of Russia actively develops the Digital ruble platform. In its 'Digital Ruble' Consultation Paper (Bank of Russia, 2020), the central bank outlined the main principles and features of the issuance of a CBDC and presented the range and key stages of the project. In April 2021, the Digital Ruble Concept was released (Bank of Russia, 2021). It specified the model of CBDC, the issuance schemes associated with it, and clarified the key steps of the project. The selected model implies that the Bank of Russia will be the sole issuer of CBDC. As a central bank liability, CBDC may be exchanged for cash or non-cash money at a ratio of one to one. Commercial banks will participate in the process by opening digital ruble wallets for their clients on a special Digital ruble platform (although these wallets will not be recorded on the banks' books, security of funds is guaranteed by the Bank of Russia). Importantly, digital ruble wallets will not pay any interest. Hence, digital rubles will primarily be used for transactions, and not as a store of value. Besides, the issue of CBDC will not add new money to the system. Rather, it will only lead to changes in the composition of broad money (CBDC will partly replace both cash and deposits). In 2022, the Bank of Russia launched the pilot of the Digital ruble platform (in a test environment) while the pilot phase with real money is scheduled for April 2023.

We consider CBDC as a means of payment and estimate a demand model using the attributes approach, which has not only become the dominant approach in payment literature, but has already been used to evaluate the demand for CBDC for Canada (Hyun et al. 2020; Li 2021). The potential demand for CBDC is crucial for the consequences of its introduction for the economy, in particular, the impact on banking sector liquidity[2]. In this paper, we analyze the potential of employing for this purpose the model we have presented. Notably, the aim of this paper is to develop

[1] In a fiat money system, the latter is created by banks when extending loans or buying assets.

[2] See, e.g., Grishchenko et al. (2021) and Grishina and Ponomarenko (2021), who discuss the implications for the liquidity of the banking sector.

the tool rather than constructing the most realistic scenario of CBDC circulation in the economy. The assumptions regarding the attributes of CBDC used in this paper rely on survey data and are illustrative.

The rest of the paper is organised as follows. Section 2 presents a review of the literature on the subject. Section 3 discusses the methodology, sources of data, and the properties of the data. Section 4 describes the model of demand for CBDC. Section 5 presents model estimates and principal findings for a variety of scenarios. Section 6 tests the robustness of the results. Section 7 concludes.

2. RELATED LITERATURE

There is a growing strand of literature that addresses the issue of potential proliferation of CBDC. The review of theses of that research below is provided to put this paper in the context of modern theoretical research and has virtually no relation to the authors' views on the issues concerning CBDC.

The majority of structural macroeconomic models of the effects of the introduction of CBDC imply that CBDC is remunerated (i.e., pays interest to its holders).[3] Hence, the income motive (or, in terms of attributes, cost) becomes the main driver of consumer choice while a number of researchers also consider the motive of safety (a CBDC is immune to theft, while cash is not, and deposits might not be repaid if banks go bankrupt) (Andolfatto 2018; Williamson 2019).

Agur et al. (2021) represent consumer payment preferences using an interval with cash and deposits at opposite ends, where cash is valued because of its anonymity, while bank deposits are valued for their safety. Several researchers use the assumption of heterogeneity of sellers (implying that they accept mainly cash for small purchases or only deposits for large ones) and avoid the use of attributes to model the shares of cash and deposits (Keister and Sanches 2019; Chiu et al. 2021). Barrdear and Kumhof (2016) mention other reasons to hold CBDC: the limits on issuance make CBDC scarce[4], and CBDC may have technological advantages over deposits. They include these features in the liquidity generation function. Kumhof and Noone (2018) propose that banks are not obliged to convert deposits into CBDC, which understates the role of demand for it. Bindseil

[3] In Russia, CBDC will not be remunerated (Bank of Russia 2020, 2021).
[4] There are no such constraints on the issue since digital rubles will be issued on demand in exchange for non-cash money.

(2020) claims that this would be inefficient and makes another proposition instead: dividing the payment and store of value functions of CBDC by tiering (paying different interest rates on CBDC holdings depending on their amount). Bindseil's proposition allows smoother control of CBDC circulation[5].

Nevertheless, we believe that, considering the features envisioned for the Digital Ruble, it would be appropriate to regard it as a payment instrument with a set of attributes and employ a corresponding modelling approach. Researchers from central banks, academia, and financial companies have conducted a number of surveys to reveal payment preferences in retail payments. The majority of research deals with consumers' preferences. Arango and Taylor (2008) emphasise the importance of evaluating of firms' preferences as well, given the two-sided nature of the market. Nevertheless, their models on payment shares reveal that merchants have little influence over the payment methods used by consumers, aside from the initial decision to accept a particular method (which, in turn, heavily relies on the economies of scale and relative usage of that payment method)[6].

The traditional approach (for instance, that of Rysman (2010)) implies regressing the relative frequencies of use of various payment methods on a number of survey respondents' characteristics, including demography, education, level of income and wealth, region of residence, etc. This strand of research, in effect, stresses the differences between various payment methods. Because it ignores the similarities between payment methods, it is unable to properly analyse consumer choice in the case of previously unseen instrument.

Borzekowski and Kiser (2008) and Arango and Taylor (2009) take a step forward, as they considered the characteristics that can be attributed to different methods of payment (attributes), while Ackerberg et al. (2007) describe in detail the use of characteristics-based demand systems to examine the effect of either price changes or new products on consumer welfare. Borzekowski and Kiser (2008) analyse the demand for a new payment instrument using the inclusion of product characteristics in the consumer utility function. By combining product attributes to form new payment options, they can calculate predictions for consumer response to hypothetical introductions to the set of choices. They find that consumers respond strongly to time elapsed at the checkout counter. They also detect that substitution patterns vary substantially with demographics. Arango

[5] In the Digital Ruble Concept this model is not considered since there is no need to replace bank services and due to the fact that digital rubles will not be remunerated.
[6] In practice, sellers often propose their clients to pay using modern payment services. Hence, the sellers can affect the choice and the respective set of attributes.

and Taylor (2009) concentrate on only two attributes of credit and debit cards and cash: convenience and risk. They find that consumers who perceive debit cards and credit cards to be more convenient and less risky than cash use them more frequently. On the whole, Borzekowski and Kiser (2008) and Arango and Taylor (2009) offer a promising avenue for other researchers.

The new, attributes-based approach[7] has enabled researchers to explain the increase in the use of cash in the USA after the Global Financial Crisis (GFC). According to Schuh and Stavins (2010), the observed decline in US cheque use was conditioned by changes in the relative cost and convenience of cheques. Foster et al. (2009), who conduct their own survey, add that the percentage of consumers who rate cash as low cost or very low cost (the top two ratings) rose from 75.2 percent to 81.9 percent, and the percentage of consumers who rate cash as secure or very secure rose from 30.8 percent to 41.4 percent. They conclude that these improvements in consumers' rating of the characteristics of cash may have contributed to the shift to cash from 2008 to 2009.

Bagnall et al. (2014) follow this route in conducting a multi-country study aimed at measuring consumers' use of cash with payment diary surveys. They find that cash is unlikely to disappear due to persistent demand for it. According to their study, cash is generally valued by consumers for its perceived acceptance, costs and ease of use. At the same time, there are cross-country differences. In Austria, Canada, and Germany, cash is rated higher than debit cards. In the USA, cash is rated the same as debit cards, while in the Netherlands, cash is rated worse than debit cards. In Canada and the USA, the authors find similar results for cash versus debit cards and cash versus credit cards. In their view, this mirrors the fact that both types of cards are perceived to have similar acceptance. In other countries, credit cards are perceived as worse than debit cards, corresponding with the authors' perception of the acceptance of credit cards in countries such as Austria, Germany, and the Netherlands.

Koulayev et al (2016) use the 2008 US Survey of Consumer Payment Choice, which asks participants about their evaluation of a number of payment methods (cash, cheque, debit/credit/prepaid card, bank account deduction) in several dimensions. It considers the following attributes: security, setup (cost of obtaining), acceptance by merchants, cost of use, control of payment time, records (the ease of tracking use), speed, and ease of use. For example, cheques score low on speed but high on record keeping, while debit and credit cards look quite similar

[7] Also known as the 'Characteristics-based approach'.

(except for cost, where debit cards look better). The authors develop a structural model which simultaneously predicts adoption and use.

A VISA survey (VISA, 2019) was conducted in the UAE. It highlights four key attributes of cards: safety, help in managing budgets, convenience (no need to carry cash), and cost (offers rewards). Another VISA survey was designed for Hong Kong, Macao, and Taiwan (VISA 2020). It considers a wide range of payment methods: cash, credit/contactless cards, mobile contactless payments, in-app mobile payments (card, wallet), and QR payments. It compares perceptions of the following attributes: safety, privacy (anonymity), availability (wide acceptance), speed, and cost (whether offers can be received and redeemed easily). Cash holds the lead in safety, privacy, and availability, while contactless cards are the quickest and enable the highest rewards.

Swiecka and Grima (2019) use a Computer-Assisted Personal Interview administered in Poland. They provide a long list of possible payment method attributes. It includes convenience (ease of use), security, speed, cost, control of spending habits, the ability to make payments at any time, acceptance, anonymity, and the ability to make payments without leaving home. The authors find that cash still in many respects has the lead in the consumer payment market mainly thanks to its ease of use. Security and speed are important as well.

The novelty of the study conducted by Paysafe holding (Paysafe 2020) is that it takes into account the impact of COVID-19 on consumer payment preferences. The authors survey 8,000 consumers from the US, the UK, Canada, Germany, Austria, Italy, and Bulgaria. The study considers a wide range of payment instruments: credit/debit/prepaid cards, digital wallets, direct bank transfers, invoice payments, eCash, and pay-by-instalment plans. The list of attributes is long as well: protection against fraud, security, cost, ease of obtaining refunds, speed, ease of use, positive impression/familiarity, acceptance, privacy, and reward/VIP programmes. The study shows that even in the time of COVID-19, consumers demonstrate a willingness to use cash even it might not be safe to handle cash during the pandemic.

The case of Russia has been thoroughly studied by the authors from the Centre of Financial Technologies and Digital Economy of the Skolkovo-NES. They have organised a number of surveys to reveal the attitudes of Russian consumers to various payment methods, including the most innovative ones. Krivosheya (2020) asks respondents about the convenience, speed, and security of cashless payments. Information about loyalty programmes, contracts with issuers, and social characteristics are used as controls. Semerikova (2019) finds that ‘a bank card has become a new must in Russia'. People tend to choose it because of its convenience, safety, and access to online purchases. Cash is mainly used out of habit or due to the unavailability or higher costs of cashless payments.

Several previous studies have already employed the attributes-based approach to analyse the demand for CBDC. Huynh et al. (2020) develops a structural model of demand for payment instruments allowing for heterogeneity in consumer preferences, which depends on transaction costs, ease of use, affordability, rewards and security. Using the Bank of Canada's Methods-of-Payment Survey, collected in 2009, 2013, and 2017, they create counterfactual scenarios to estimate post-introduction consumer adoption and use of new payment instruments. Their counterfactual simulations suggest that a CBDC may be used at points of sale with probabilities ranging between 0.19 and 0.25. The authors note that high adoption does not necessarily mean frequent use, since consumers might want to have an instrument but not use it. In all scenarios, the predicted use rate does not reach 10 percent until at least 60 percent of merchants accept the new payment instrument. They additionally conclude that the introduction of a CBDC would make a small but meaningful contribution to the welfare of Canadians. Li (2021) has also evaluated the consumer demand for CBDC under different scenarios by applying a structural model to two unique household survey datasets: the Canadian Financial Monitor during the 2010–2017 period and the Methods of Payment survey for the year 2013. The utility of holding CBDC also depends on the differences between CBDC, cash, and deposits in terms of their attributes. Under the baseline scenario, households prefer to hold between 4% and 54% of their liquid assets in CBDC (the precise value depends on how households with different characteristics value the CBDC). In this paper, we follow similar route by empirically estimating the values of the attributes of various payment methods and then constructing scenarios for the use of CBDC in Russia.

It is worth noting that the attributes approach has been used not only in cases where CBDC was regarded as a payment medium but also where it assumed to be a store of value. This enables the enhancement of the analysis, especially in situations where the possibility of CBDC remuneration is unclear. Bijlsma et al. (2021) find, using data from a representative panel of Dutch consumers, that virtually 50% of consumers would open a CBDC electronic wallet, and the same holds for a CBDC savings account. Interestingly, the proportion of people willing to open a CBDC wallet is highest among those who value privacy and security the most and who do not trust banks. The authors also emphasise the importance of proper communication about any CBDC and its properties.

The Bank of England (2021) employs the attributes approach to the estimation of an illustrative scenario of the demand for new forms of digital money (such as stablecoins), the resulting responses of banks, and the impact on credit conditions. It notes that the non-financial factors which here we call attributes (convenience, trust, and safety) play a major role in determining such demand. According to Bank of England estimates, around 20% of household and non-financial deposits will be transferred to new forms of digital money.

3. METHODOLOGY AND DATA

3.1. Questionnaire

The demand for various payment instruments is modelled using the attributes method (Hyun et al. 2020; Li 2021). This approach is based on a set of characteristics (attributes) which affect the choice of a particular payment instrument in transactions. For example, it is assumed that if a payment instrument has a lower risk of loss of funds (due to possible storage loss, theft, or fraud), then it will be used more often, other things being equal.

Having reviewed the available surveys from various countries, aggregated similar categories, and taken into account the specifics of Russia, we have constructed a list of the most relevant attributes of payment methods.[8] These include: safety (security), convenience (easy access and use, high speed, ability to make payments at any time and without leaving home), cost (or/and rewards, with the opposite sign), availability (affordability, wide use and acceptance), and control of expenses.

Security covers the risk of the loss of funds described above. Convenience represents the ease and simplicity of use of the payment method in everyday life, such as the lack of a need to memorise PIN codes, and the simple habit of paying with one method or another. The presence of various kinds of bonuses (cashback, discounts, etc.) and costs (service charges) is reflected in the cost of use. Network and environment effects, such as the ability to pay for goods and services using the payment instrument anywhere or to receive salaries (by card or in cash), are included in the availability attribute. The last attribute covers the ability to control expenses effectively. People paying with cards can fully track their spending history, if necessary, which is more difficult when using cash. Note that there is a very thin line between some attributes, and it is sometimes difficult

[8] Foster et al (2009), Koulayev et al (2016), TSYS (2016), Esselink and Hernandez (2017), Caddy et al. (2020), Bundesbank (2018), Swiecka and Grima (2019), Tagat et al (2019), VISA (2019, 2020), Vegso et al (2018), Paysafe (2020).

to separate one from another. For example, the ability to pay in the nearest store can be assigned by people not only to availability, but also to convenience.[9]

In this paper, to assess the impact of characteristics on the share of a payment instrument in the number of transactions for payment for goods and services, two payment instruments are used: cash and bank cards. At the same time, 'bank cards' here means a wide range of banking services, including not only payment by plastic card, but also payment by smartphone, as well as through a banking application. Since the survey was conducted, other forms of payment have been actively developing, inter alia, Faster Payments System (SBP). Nevertheless, it was not possible to evaluate their impact at the time of the survey.

Unfortunately, we do not have direct data on consumer transactions (as, for example, in Huynh et al. (2020)), so we use data from the Bank of Russia's 2021 extensive survey on people's attitude to various means of payment, either cash or cashless (hereinafter – the DCC survey). The survey includes answers to questions such as 'Do you have a bank card?', 'Do you prefer to use bank cards to pay for goods and services[10] or to withdraw the necessary sums of cash to make payments?', 'Why do you choose cash as a payment method?', as well as estimates of the five attributes described above and the individual characteristics of respondents (age, gender, education, locality, etc.). Appendix 1 presents the most relevant questions for this research and their answer options. It should be stressed that we use the data on the number of transactions of households as a dependent variable (not a total value of transactions or stock variables such as cash in circulation or balances on bank accounts).

Based on the survey data, we divide the respondents into five groups: those with no bank cards, those who pay for almost everything in cash ('I usually withdraw the necessary sum to pay cash'), those who pay for most goods and services in cash ('I most often withdraw the necessary sum to pay cash'), those who pay for most goods and services with cards ('I most often pay for goods and services with a bank card'), and those who pay for almost everything with cards ('I

[9] We do so to balance the network attributes in the case when the attributes are built on the basis of direct answers about the advantages of payment instruments (see below).

[10] Despite the fact that transactions for payment for goods and services are only a part of all transactions, their share is large enough to be a good approximation to the entire population. For example, the share of transactions for payments for goods and services with cards in the total number of household transactions with cards was approximately 78% in the first half of 2021, according to National Payment System statistics. At the same time, the share of the value of transactions for payments for goods and services amounted to 32% (while the share of cash withdrawals totaled 22% and the rest 46% accounted for other operations).

prefer to pay for goods and services with a bank card') — see Tables A4 and A5 in Appendix 1. These groups are further used to build a model with ranked classes.

The attributes of payment methods are non-observable and could be evaluated using methods of revealing consumer preferences. We use both direct and indirect methods in our study.

A **direct method** implies asking survey respondents about the factors they regard as most important when choosing the appropriate payment method (see Tables A2 and A3 in Appendix 1). As a result, a full list of factors which matter in particular situations could be constructed. However, there are limitations that we cannot avoid (see Section 3.2 for survey details). The factors mentioned are implicitly given equal weights, and so important information may be lost. Also, respondents are usually allowed to mention only several (up to five) factors, not the full set.

In employing an **indirect method**, we reformulate the problem: respondents are provided with a list of factors which researchers consider most important based on international experience and economic intuition (see Table A1 in Appendix 1). This method also has weaknesses. Essentially, respondents are asked to rate, on a four-point scale (from 0 to 3), the safety, convenience, cost of use, availability, and ability to effectively control costs for each instrument. However, this approach in no way takes into account the importance of the attribute in the decision-making process (i.e., it describes adoption rather than use). In other words, respondents may ignore some factors in making their decisions, so the method speaks to their general attitude, and not necessarily to their payment decisions. For example, someone may highly rank the ability to control expenses using cards but not have this factor influence his or her decision in any way regarding the choice of payment instrument, while for someone else, on the contrary, it may be one of the key factors.

In our modelling exercise (described in Sections 4 and 5), we employ two alternative sets of attribute variables constructed based on both direct and indirect questions. In the case of indirect questions, the construction of the variable is straightforward, as each question corresponds to one of the five attributes. In the case of direct questions, we aggregate the responses into the respective categories (the baseline aggregation scheme is presented in Tables A6 and A7 in Appendix 2).

To estimate the demand for CBDC, we consider several scenarios with different potential sets of attributes and, based on the scoring model described below, calculate the share of the new instrument. It is worth noting that the resulting estimate, even with all modelling assumptions, should be viewed precisely as the share of the new instrument on the available dataset. To see how representative our sample is, we show the data characteristics and compare the distributions of various individual characteristics from the dataset with the distributions for the country as a whole in the next two subsections.

3.2. Survey results

The Bank of Russia's DCC survey aims at identifying the payment preferences of Russian citizens and assessing the role of various means of payment in the Russian economy. Magram MR Company conducts the survey annually in January–February. The survey is held on a regular basis and its main aim is to study the drivers behind the dynamics of cash in circulation. The questions of the survey were formulated accordingly. We were able to add the limited number of new questions only, not to change the remaining ones[11].

The survey is a collection of personal formalised interviews (the sample covers 52 constituent entities of the Russian Federation from all federal districts). The latest survey [12], held in January–February 2021, additionally included questions about preferences between cash and non-cash money (indirect method).

Importantly, the results of the survey indicate that there is substantial diversity among the respondents in terms of their payment instrument preferences. Therefore, we believe that this dataset gives us a good basis to estimate the demand model. In addition, some preliminary observations may be made by examining the raw data.

According to the survey, bank cards are superior to cash in the sense that every attribute-of bank cards are ranked on average higher by the respondents. The majority of adult Russians have one or more bank cards. Among those who do not, the older age group and people with low incomes prevail. Over the past few years, the share of those who have more than one bank card has grown. The vast majority of those who have bank cards (86%) have their wages, pensions, or social benefits paid on their cards.

Still, cash remains a popular payment instrument. According to the 2021 survey results, the percentage of citizens who make cash payments at least several times a week was 61%. Only a quarter (25%) make daily cash payments, and another 36% say they pay for goods or services in cash several times per week. Those who use cash several times per month or less amount to 33%

[11] It was important to make the results of surveys comparable over time.
[12] The latest survey available at the moment of calculations was conducted in 2021.

of Russians, of whom 25% use it several times per month, 4% use it several times every three months, and another 4% use it several times per year[13].

The most high scored attributes of non-cash, in respondents' view, are convenience and availability. Convenience has also the highest rank for cash. Summary statistics on the questions about the attributes of cash and non-cash and the distribution of responses to the questions about the attributes can be found in Appendix 1 (see Figures A1, A2, and A3).

The 2021 DCC survey also provides information on the use of payment methods (see Figures A4–A7 in Appendix 1).

3.3. Cross-check of representativeness of data

The representativeness of survey data (as compared to the whole population of the country) must be verified in order for it to be relied upon. We check this by plotting graphs of the univariate and joint distributions of the socio-demographic characteristics of the people polled and those of the population as a whole. Below, we consider univariate and several[14] two-dimensional distributions of the following socio-demographic factors: age, city type, education, employment, income, region, and sex. We use a truncated dataset which excludes respondents who replied 'not sure' to one or more questions of interest. In general, the main characteristics of the variables of the sample conform to those of the population (see Figures A8–A19 in Appendix 1).

4. MODEL

We assume that each instrument (i) is assigned its own score (s_n^i) by each person (n), which is formed using its attributes (a_n^i) and a set of additional features (X_n), such as age, gender, locality, etc., as well as a random factor (ε_n^i):

$$s_n^i = \beta_0^i + \beta_a a_n^i + \beta_X^i X_n + \varepsilon_n^i$$

The share of instrument (sh_n^i) in the transactions of the n-th individual is determined based on the score of the instrument and those of other instruments according to the formula:

[13] Notably, cashless settlements for goods and services, including those using new methods of payment such as virtual bank cards and SBP, increase the share of cashless payments in the households' structure of payments. By the end of the Q3 2022 their share amounted to 77,7% (according to National Payment System statistics).
[14] Official statistics offers us only a number of two-dimensional distributions.

$$sh_n^i = \frac{e^{s_n^i}}{\sum_{j=1}^{N_I} e^{s_n^j}}$$

where N_I is the number of available payment instruments (two during the estimation and three during the scenario analysis). Scores are non-observable and are estimated so as to match share ranges which are based on the survey values assigned to classes (see below). The more a consumer values a certain attribute (except for cost), the higher the score and the higher the share of the instrument in payments.

To estimate the model, each class (k) is assigned a range $(\mu_k^{low}, \mu_k^{up})$, within which the proportion of bank card transactions takes its values. It is assumed that the random factor has a normal distribution with zero mean and estimated variance (σ^2). The likelihood of the model is written as follows:

$$\sum_{n=1}^{N}\sum_{k=1}^{K} I_n^k \log\left(F_{2\sigma^2}\left(\mu_k^{up} - s_n^{card} + s_n^{cash}\right) - F_{2\sigma^2}\left(\mu_k^{low} - s_n^{card} + s_n^{cash}\right)\right)$$

where I_n^k is the indicator that the share of the bank card transactions of the n-th individual falls into class k and $F_{2\sigma^2}$ is a cumulative normal distribution with a variance of $2\sigma^2$.

The model described is up to a re-parameterisation equivalent to an ordered probit model with constraints on the boundaries between classes. In addition, unlike the classical ordered probit model, we do not impose restrictions on the absence of intersection between class ranges (difference in fixed effects), i.e., μ_k^{low} does not have to equal μ_{k-1}^{up}.

5. RESULTS

This section presents the main results of the paper. The first part describes the model specifications selected and the estimated parameters. The second part is devoted to scenario analysis.

5.1. Model estimation

All five classes are preserved in the baseline model. The ranges of the percentage of payments made with cards for the answer groups ‘pay for almost everything in cash’, ‘pay for most goods and services in cash’, ‘pay for most goods and services with cards’, and ‘pay for almost everything with cards’ are chosen uniformly from zero to one, i.e., the first group receives shares from 0 to 0.25, and the last group receives shares from 0.75 to 1. The share of payments for people who do not pay with cards should be equal to zero, however, the proposed scoring model does not allow the setting of an explicit zero share, so a small range around zero is set for the fifth class[15].

For the sake of simplicity, we do not use any control variables in this section. The next section, which tests the robustness of various model assumptions, shows that this has virtually no effect on the results. Additional analysis shows that individual payer characteristics are almost uncorrelated with the attributes. This means that control variables could only affect the results by reducing the variance of the noise. The attribute coefficients remain almost unchanged.

Table 1 presents the parameter estimates of two alternative models. The first version employs a measure of attributes constructed based on the responses to the indirect questions in the survey (the ‘Attributes’ column in the table, indirect method). The second version employs a quasi-attribute measure constructed based on the responses to the direct questions in the survey (the ‘q-Attributes’ column in the table, direct method). Although in both approaches the attributes are normalised to be between 0 and 3, the scores are not comparable to one another. Nevertheless, Table 1 shows that all the coefficients for the attributes have intuitively correct signs. Increases in security, convenience, availability, and the ability to control spending increase an instrument's share in the total number of transactions, while increases in the cost of use decrease a payment instrument's share. Moreover, only one of the ten coefficients (cost of use in the first column) turns out to be insignificant at the 90% confidence level. All this signals that the results are adequate and allows us to hope for estimates close to the real values in our scenario analysis.

The estimates can be interpreted as follows: if the coefficient for ‘control of expenses’ by the indirect method equals 0.28, this means that if a new instrument allows significantly better control over expenses (i.e., the reply changes, for example, from ‘agree’ to ‘fully agree’), the score of the new instrument increases by 0.28, which contributes to the growth of its share in payments (the extent of which can be easily calculated from the relation of shares and scores).

[15] As an additional representativeness check, we compared the average share of card payments (weighted by income and number of transactions, and simply averaged without weights) with the official statistics using the midpoints of these intervals. The difference in the results is insubstantial.

Table 1. Coefficient estimates for models (90% confidence intervals)

	Attributes	q-Attributes
Constant	0.65 [0.53;0.77]	0.22 [0.09;0.34]
Security	0.19 [0.07;0.31]	0.19 [0.11;0.27]
Convenience	0.45 [0.31;0.6]	1.5 [1.33;1.67]
Cost	-0.08 [-0.2;0.03]	-0.33 [-0.42;-0.23]
Availability	0.39 [0.27;0.51]	0.31 [0.24;0.38]
Control of expenses	0.28 [0.17;0.39]	0.22 [0.16;0.28]

5.2. Scenario analysis

We use a simulation analysis to consider scenarios. As part of the simulations, the difference between the scores of cards and cash ($s_n^{card} - s_n^{cash}$) is calculated for each individual and an assumption about the score of the CBDC (s_n^{CBDC}) is made. A random factor is then added to the scores[16].

Among the many possible scenarios, we consider the following four:

1. *A*: the new instrument has the same fixed effect as cards, but all attributes are maximal for all people.

2. *B*: the new instrument has the same fixed effect as cards, but all attributes are minimal for all people.

3. *C*: the new instrument has the same fixed effects as cards and the same level of security and control of expenses, but has slightly worse characteristics in terms of convenience, and slightly better characteristics in terms of cost of use and availability.

4. *D*: the new instrument has the same fixed effect as cards and the same level of security, but other characteristics (convenience, cost, availability and control of expenses) are slightly worse.

[16] Note that we do not take into account the posterior distribution of the difference of random factors. Instead, the difference is simulated according to the model assumptions.

In all scenarios, it is assumed that the new instrument is similar to cards in terms of its fixed effects. Indeed, digital currency has more in common with bank cards than with cash. Like cards, it requires digital infrastructure, but it could potentially have absolutely the same (and even better) merits, such as the ability to pay remotely or control expenses, so it is realistic to assume that a digital currency would be, in general, similar to cards[17].

Since the purpose of this paper is to demonstrate the capabilities of the tool used to estimate CBDC demand rather than to focus on specific attribute values in a particular scenario (which can easily be adapted to new assumptions), scenarios A and B are designed to outline the boundaries of the possible values for the share of a new instrument. Scenarios C and D estimate expected demand in equilibrium after a transition period.

For the first method (indirect), in scenario C convenience is reduced by 1 point as compared with that of cards (a shift from a higher category to the one below it, e.g., from ‘fully agree’ to ‘agree’) if they were positive, while availability is increased by 1 point and the cost of use goes down by 0.5. This scenario is based on the assumption that the new instrument will be slightly worse in terms of convenience, for example, due to the habit effect (people are less willing to use new technical solutions even if they are not inferior to existing ones). While the Digital Ruble project doesn’t imply the possibility for CBDC holders to participate in bonus programmes, its overall cost of use is assumed to be lower. For this scenario, we assume that economy relative to cards from reduced user charges will have a greater impact on the cost of using CBDC than the absence of bonus programmes on average. It is also assumed that the availability of CBDC to be higher than that of cards with the appearance of C2C offline payments. Similar assumptions are laid in the method based on direct questions (see Appendix 2 for details).

In scenario D, we assume for the indirect method that convenience, availability and control of expenses are reduced by 1 point if they were positive while cost rises by 0.5 point. Despite the benefits of digital ruble from the savings on servicing described above, here we assume that the effect of the lack of bonus programs will be greater. It is also implied here that the share of C2C offline transactions is negligible, while the network effects (due to worse other characteristics fewer people will use the Digital Ruble and the share of digital ruble in wages will be inferior to

[17] Digital rubles will have even more in common with Faster Payments System (SBP) where the Bank of Russia serve as an operator (as in the case of the Digital ruble). At the same time, these two instruments are not identical (for instance, digital rubles may be used for offline payments). Taking into account this as well as the fact that in 2021 SBP was primarily used for money transfers between individuals, we do not use the data on SBP transactions in our calculations.

that of cards) and possibly lower acceptance in retail outlets will lead to lower prevalence, which will reduce availability. As a consequence, this will partially affect the ability to control spending. As for scenario D, similar assumptions are also made for the direct method (see Appendix 2 for details).

Figure 1. Scenarios for the indirect method (Attributes)

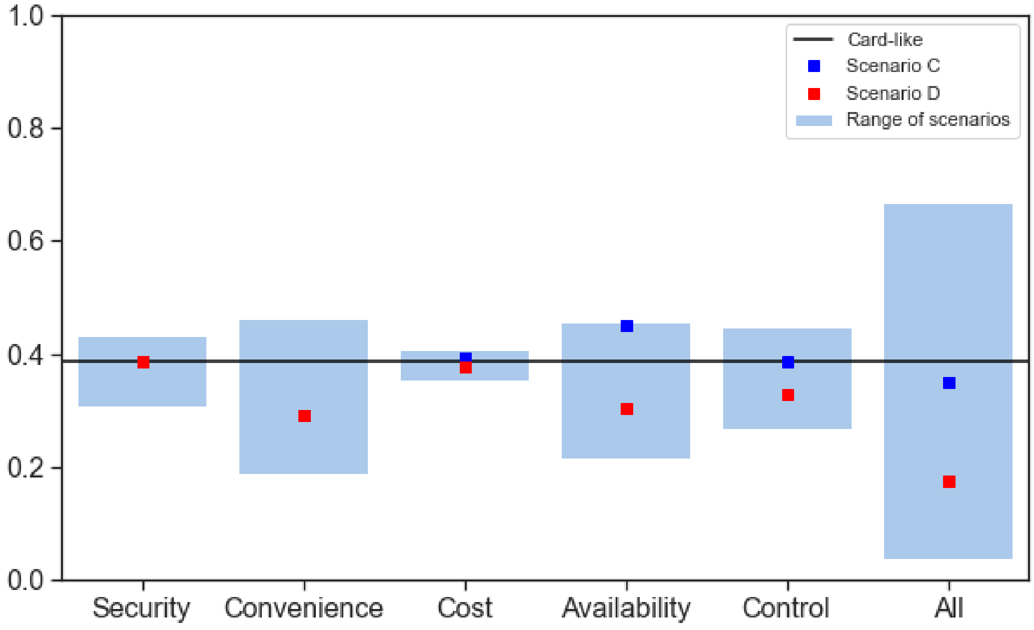
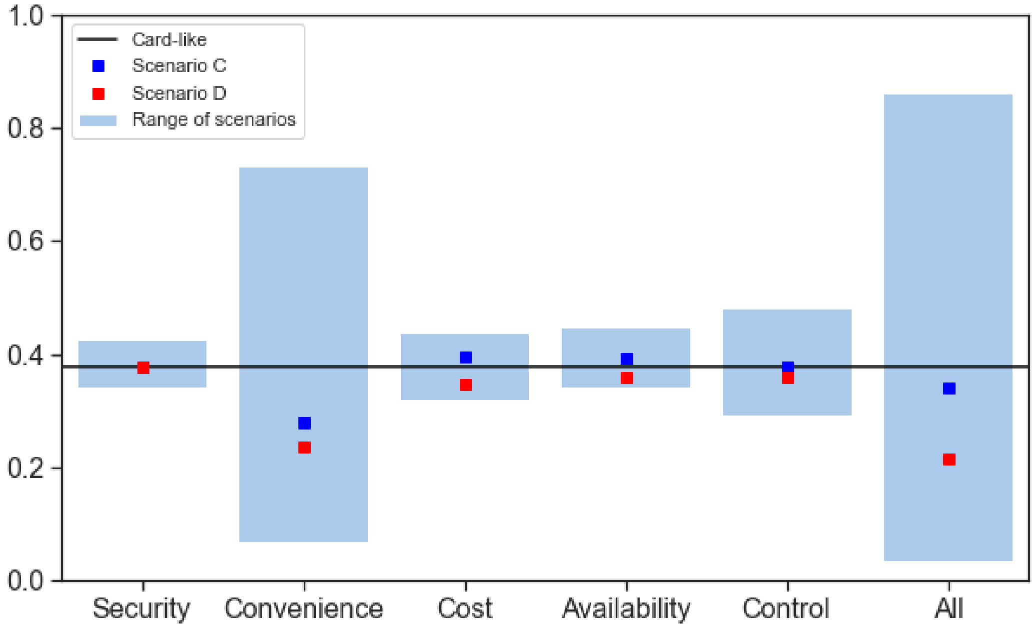


Figure 2. Scenarios for the direct method (q-Attributes)



The results of the simulations for the different scenarios are shown in Figures 1 and 2. It can be seen from the figures that both methods allow the simulation of a wide range of scenarios from the point of view of the final result (the ‘All’ column). In scenario C, estimates of shares of 35% and 34% are obtained for the first and second attribute scoring methods, respectively. In scenario D, the shares are smaller amounting to 18% and 21%, respectively. In both scenarios and methods, convenience is the greatest contributor. Availability also makes a significant contribution for the indirect method. The lack of such contributions in the second method may be partially explained by the fact that some of the questions that could potentially be attributed to both availability and convenience were assigned to convenience in order to make the availability attribute as balanced as possible, but in the next section, we will show that a different partitioning leads to a minor rebalancing of the effect between the two attributes.

There is an additional uncertainty associated with the estimates obtained. It arises from the assumption that the fixed effects of a CBDC would be the same as for bank cards (which of course can be weakened in the scenario analysis if necessary). On the one hand, the initial demand for CBDC is likely to be lower owing to the role of habit (which we may not have fully considered in scenarios regarding attributes). People tend to prefer traditional payment instruments when their attributes are not dramatically different from those of new ones. For instance, a Skolkovo-NES consumer survey shows that only 43% of bank card holders use smartphones to make payments even though 76% of bank card holders have smartphones with a contactless payment function (Skolkovo-NES 2017). In other words, the discrepancy between payment frequencies is much larger than that implied by the differences between the attributes of bank cards and smartphones. This observation may be regarded as an indication of the expected lag in the dissemination of a CBDC after its initial introduction. On the other hand, the demand for CBDC might be higher in particular environments (for example, if government social payments are carried out in CBDC or if the CBDC becomes trendy). In addition, the demand for CBDC might be higher if it starts to perform unexpected functions, such as, for example, as a store of value.

6. ROBUSTNESS CHECKS

In this section, we test the robustness of our results to various modelling assumptions, such as the presence of control variables, the distribution of direct answers across attributes, changes in the survey period, the inclusion of the group that does not have bank cards in the model and potential model non-linearity. To save space, the robustness checks are presented only for scenario D, as for the scenario with the largest deviation from the share of cards in the 'All' column.

In the previous section, control variables were excluded from the analysis. On the one hand, this increases the number of observations for the estimation of each coefficient, but on the other hand, it introduces the risk of missing variables, which may lead to incorrect estimates of the impact of attributes on the shares of payment instruments. Table 2 shows the results of the estimation of the model coefficients with control variables (the 'Attributes with controls' and 'q-Attributes with controls' columns) for region, gender, age, and other payer characteristics. It is easy to see that the coefficients remain almost the same, which indicates the possibility of excluding these variables from the calculations. Additional analysis shows that these variables do not correlate with attributes, and the only way they can affect scenario exercises is by reducing the variation of the random factor. However, Figures 3 and 4 show that this does not happen.

Table 2 and Figure 4 also show that, for the direct method, the results are unchanged if the questions about the possibility of card payments in stores and about remote payment are moved from the convenience to the availability category (q-Attributes.v2).

As mentioned above, we estimate the model using the data from the 2021 survey, which, unlike previous surveys, was conducted after the pandemic began. This may significantly affect our results, as some patterns in the use of cash or card payments may have been caused by temporary factors associated with the pandemic. To test the significance of these factors, we run an analysis on direct questions about the reasons for choosing payment instruments (q-Attributes), which were also present in the 2020 survey[18]. Figure 4 shows a 5 p.p. difference from the baseline model. This occurs for two reasons. First, the average share of card payments in 2020 was smaller, which creates a lower base effect. That is, a payment instrument identical to cards will take a smaller share. Second, convenience has a stronger effect on payment instrument choice in the 2020 dataset (q-Attributes 2020 column in Table 2) than in the 2021 dataset, resulting in a larger decrease compared to the card-like scenario for the less convenient digital instrument.

The group of individuals who do not have bank cards was included in the baseline model. This implicitly contains the assumption that an individual's choice of payment share is described by the one-step model outlined above. An alternative is, for example, the model proposed in Huynh et al. (2020), where the authors divide the selection process into the steps of identifying a pool of payment instruments and then selecting an instrument from the pool. To test robustness to this type of assumption, we estimate a model where the group without cards is excluded. Such a method essentially replaces the second step from the work of Huynh et al. (2020). In our scenario analysis,

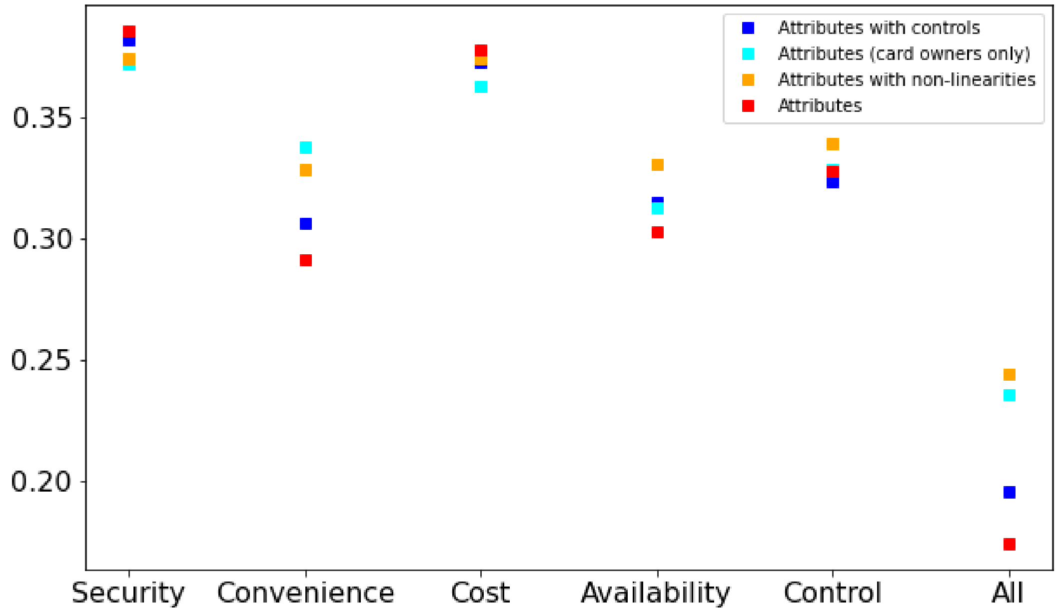
[18] As noted in subsection 3.2., there were no indirect questions in the survey held in 2020.

we assume that people belonging to this group will not use the Digital Ruble. Table 2 and Figures 3 and 4 demonstrate that excluding the zero group results in less scenario sensitivity to changes in attributes, and especially to convenience (the ‘Attributes (card owners only)’ and ‘q-Attributes (card owners only)’ columns). This is due to the fact that for the group with zero card transactions, the score was significantly negative, and this, in turn, led to an increase in parameter estimates. For both methods, the resulting estimates are about 5 p.p. higher than in the baseline model.

The model presented in Section 4 is linear in the sense that scores depend linearly on attributes. This assumption can be very strong, so in Appendix 3 we extend the model to the case where the dependence of scores on attributes is non-linear. Figures 3 and 4 show results ('Attributes with non-linearities' and ('q-Attributes with non-linearities') where Random Forest (Brieman (2001)) was used as the non-linear model. Although the overall estimates of the contribution is 6 p.p. higher than for the main model for the indirect method, in general we see that the results are relatively similar19.

The robustness checks presented show that the results of the analysis may be both above and below the baseline model, but they do not differ dramatically, which allows us to hope for the adequacy of its predictions in our scenario analysis.

Figure 3. Robustness check for the indirect method, scenario D



[19] We also did not see much difference in the predictive power of the linear and non-linear models.

Figure 4. Robustness check for the direct method, scenario D

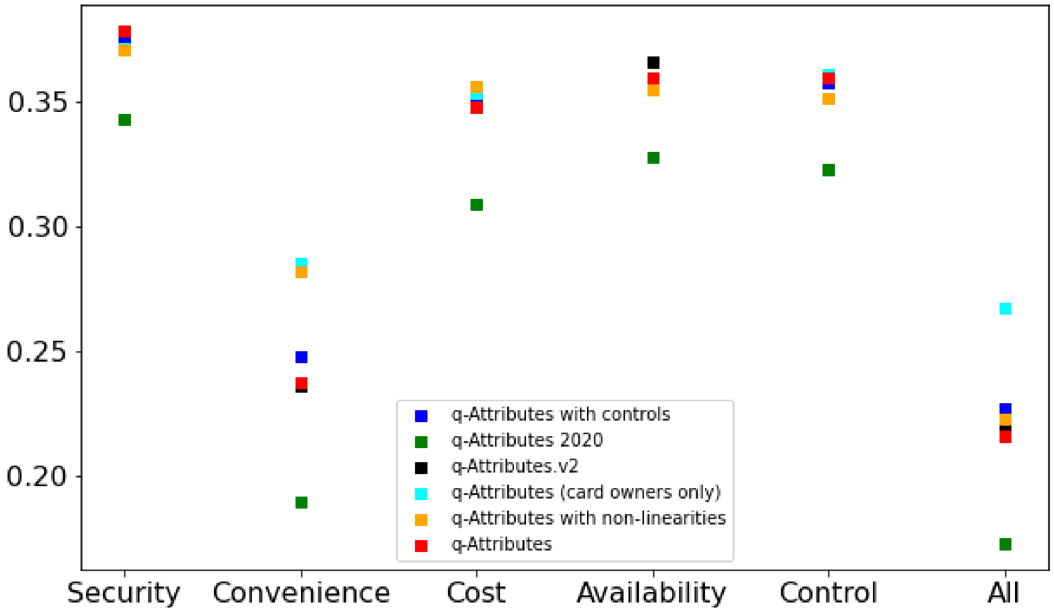


Table 2. Robustness check for estimates of coefficients (90% confidence intervals)

	Attributes	Attributes with controls	Attributes (card owners only)	q-Attributes	q-Attributes with controls	q-Attributes 2020	q-Attributes. v2	q-Attrib-utes (card owners only)
Constant	0.65 [0.53;0.77]	-	0.85 [0.75;0.94]	0.07 [0.03;0.11]	-	0.01 [-0.02;0.05]	0.07 [0.03;0.11]	0.20 [0.16;0.23]
Security	0.19 [0.07;0.31]	0.17 [0.06;0.29]	0.10 [0.01;0.19]	0.19 [0.11;0.27]	0.18 [0.11;0.26]	0.22 [0.14;0.30]	0.19 [0.11;0.27]	0,15 [0.09;0.21]
Convenience	0.45 [0.31;0.6]	0.36 [0.22;0.5]	0.17 [0.06;0.27]	1.5 [1.33;1.67]	1.33 [1.16;1.5]	1.92 [1.73;2.10]	1.38 [1.22;1.54]	0.85 [0.72;0.98]
Cost	-0.08 [-0.2;0.03]	-0.09 [-0.2;0.02]	-0.10 [-0.18;-0.01]	-0,33 [-0.42;-0.23]	-0,26 [-0.35;-0.17]	-0,40 [-0.49;-0.31]	-0,33 [-0.42;-0.23]	-0.19 [-0.26;0.12]
Availability	0.39 [0.27;0.51]	0.32 [0.2;0.43]	0.29 [0.20;0.38]	0.31 [0.24;0.38]	0.27 [0.2;0.34]	0.30 [0.23;0.37]	0.40 [0.31;0.50]	0.19 [0.14;0.25]
Control of expenses	0.28 [0.17;0.39]	0.28 [0.17;0.39]	0.22 [0.14;0.30]	0.22 [0.16;0.28]	0.21 [0.15;0.27]	0.31 [0.25;0.37]	0.22 [0.16;0.28]	0.09 [0.07;0.12]

7. CONCLUSIONS

Projecting the potential demand for CBDC is crucial for the assessment of the consequences of its creation. As long as there remain no actual cases of CBDC implementation available for analysis, researchers have to employ indirect approaches to evaluating the demand for this new payment instrument. These approaches involve the estimation of demand models for existing instruments and using it to estimate the consequences of the introduction of an additional hypothetical instrument (representing the CBDC) with certain proposed characteristics. In this paper, we have conducted a similar exercise for Russia.

We estimated a model of households' use of alternative payment instruments (cash and bank cards). In our modelling set-up, households' preferences are determined by the instruments' attributes and, hence, choices regarding payment methods depend on the differences in these attributes between instruments. The results indicate that consumer choice is quite sensitive to the perceived attributes.

Based on the robustness check and interpretability of results, we believe that the estimated model can be used as a starting point for forecasting demand for CBDC conditionally on its expected design and consumers' perception of it. We discuss several illustrative projections to demonstrate the application of the tool developed. Depending on the hypothesised attributes, the predicted utilisation of CBDC varies considerably, although under conservative assumptions, the projected use of CBDC in household transactions is limited.

In this paper, we focus on the demand for CBDC in terms of the number of transactions of households. The analysis of demand for CBDC in terms of value of transactions or the share of the new instrument in the broad money requires additional assumptions about the use of the instrument by other economic actors and the velocities of various forms of money, and goes beyond the scope of this paper.

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Appendix 1

Table A1. Questions about respondents' perceptions of cash/non-cash payment instruments (list of attributes constructed by researchers)

№	Statement	Fully agree	Agree	Disagree	Fully disagree	Not sure
Q46.1	Cash/bank cards are **safe**, the risk of losing money while holding them or in operations with them is low	3	2	1	0	99
Q46.2	Cash/bank cards are **convenient**: easily accessible, easy to use, money transactions require no effort	3	2	1	0	99
Q46.3	Cash/bank cards are **costly**: it is expensive or unprofitable to use this method of payment	3	2	1	0	99
Q46.4	Cash/bank cards are **available**: they are widely used by people I know, by the stores where I go shopping, and by retail organisations	3	2	1	0	99
Q46.5	Cash/bank cards help me effectively **control expenses**	3	2	1	0	99

Source: Questionnaire of the DCC survey ‘People’s attitude to various means of payment’.

Table A2. Why do you choose cash as a payment method? Choose 5 or fewer

№	Factors
1	Cash helps me effectively **control my expenses**
2	I **used to** pay cash
3	I believe that it is **faster** to pay cash
4	It is **easier** for me to pay cash (I don’t have to memorise a PIN, etc.)
5	I believe paying cash is **safer** (I’m afraid of bigger withdrawals from my accounts or the theft of personal data)
6	I like to count banknotes **manually**, to **hold them in my hands**
7	Outlets are more willing to **accept** cash
8	It is **cheaper** to use cash (I don’t have to pay for servicing cards)
9	I’m afraid of **technical failure**
10	I **receive my income** in cash
11	I’m **not able** to use non-cash (please indicate the reason)
99	Not sure

Source: Questionnaire of the DCC survey ‘People’s attitude to various means of payment’.

Table A3. Why do you use a bank card as a payment method? Choose 5 or fewer

№	Factors
1	A bank card helps me effectively **control expenses**
2	I don’t have to **carry around** a lot of cash
3	I believe that it is **faster** to pay with a card
4	It is **easier** for me to pay with a card (I don’t have to count banknotes and coins, etc.)
5	With a card, I can effect **distant** payments (mobile bank, internet bank)
6	I believe paying with cards is **safer** (bank cards are protected better)
7	I can participate in **bonus, discount, or cashback programmes**
8	It is **cheaper** to use cards (for instance, I get back part of the sum)
9	Cash is **dirty and unsanitary**
10	I **receive income** in a card account and I **don’t want to waste time** on cash with-drawals
11	**Other** (please specify)
99	Not sure

Source: Questionnaire of the DCC survey ‘People’s attitude to various means of payment’.

Table A4. Do you have a bank card?

№	Answer
1	Yes
2	No

Table A5.Do you prefer to use bank cards to pay for goods and services or to withdraw the necessary sums of cash to make payments?

№	Answer
1	I prefer to pay for goods and services with a bank card
2	I most often pay for goods and services with a bank card
3	I most often withdraw the necessary sum to pay cash
4	I usually withdraw the necessary sum to pay cash
99	Not sure

Figure A1.
Do you agree with the following statements about cash?
(All respondents, n=2500)

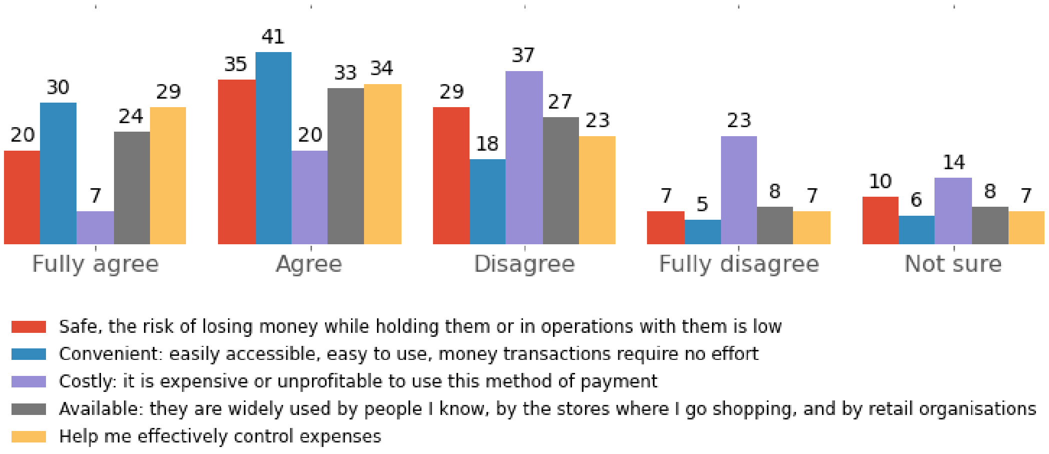


Figure A2.
Do you agree with the following statements about cashless instruments?
(All respondents, n=2500)

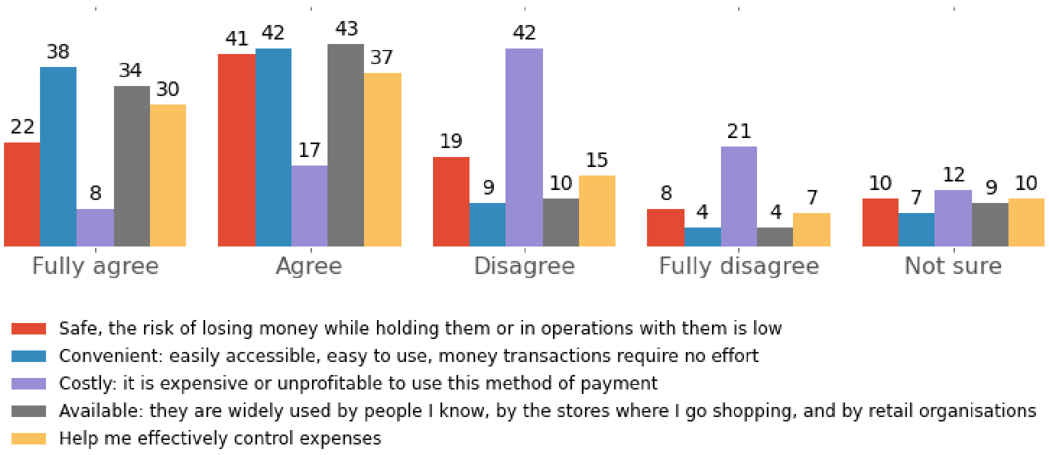


Figure A3. Statistical properties of responses to questions about attributes of methods of payment

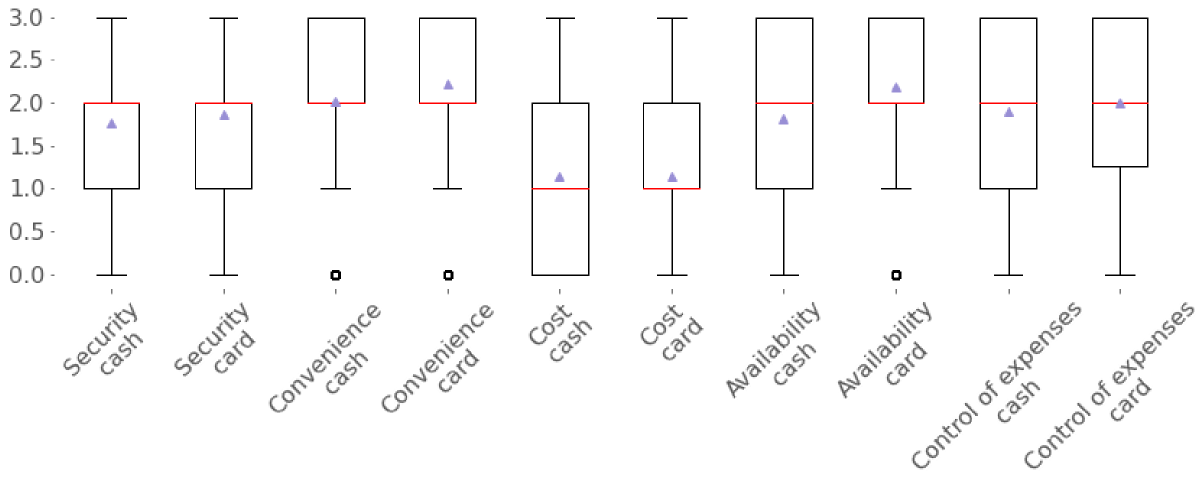


Figure A4.

Do you have a bank card?

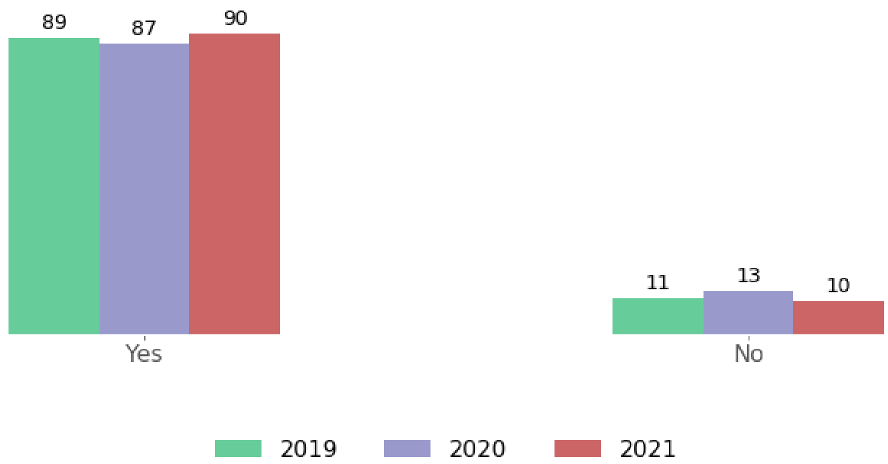


Figure A5.

Do you prefer to use bank cards to pay for goods and services or to withdraw the necessary sums of cash to make payments?

(respondents who have bank cards)

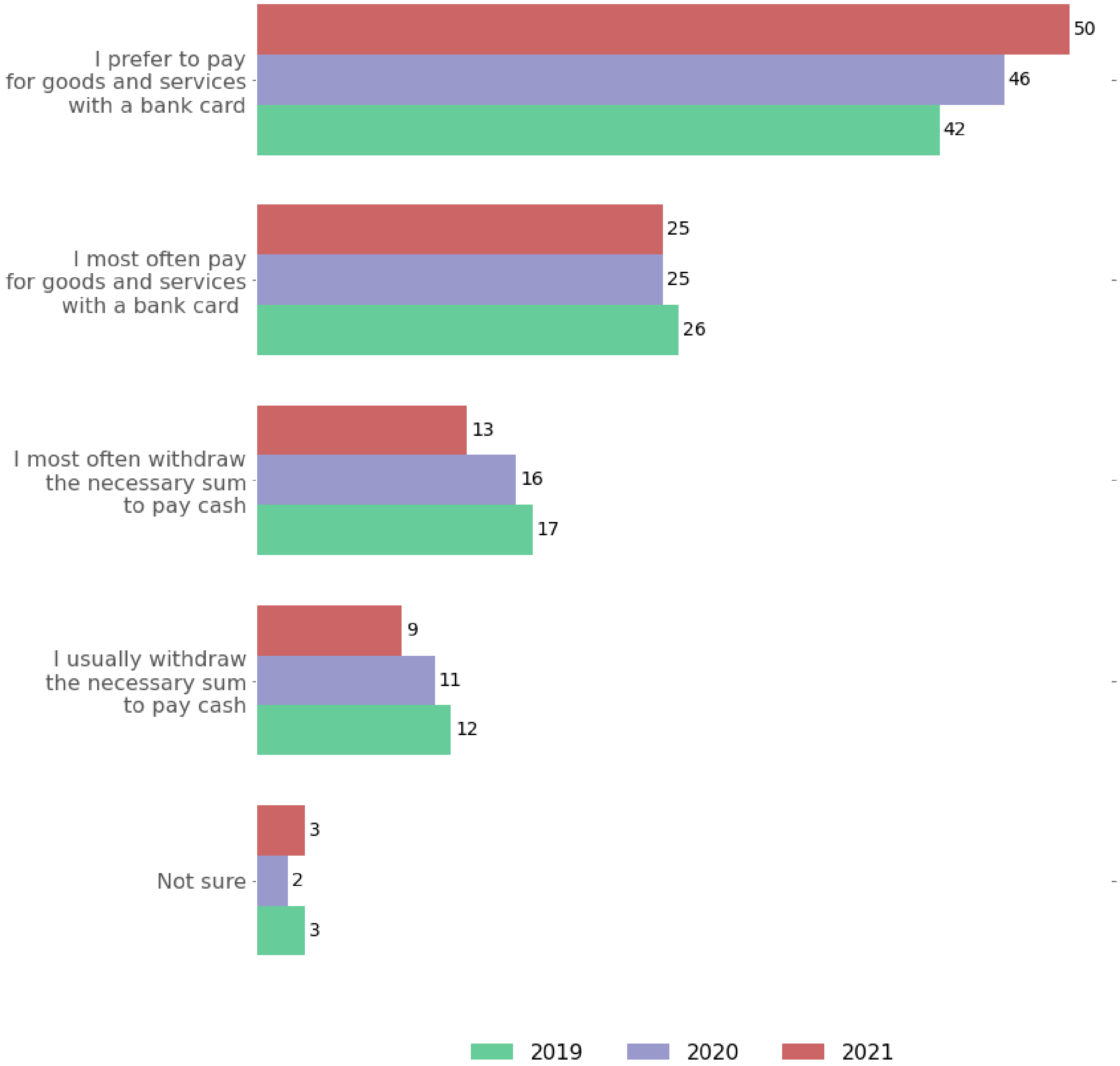


Figure A6. Why do you choose cash as a payment method?

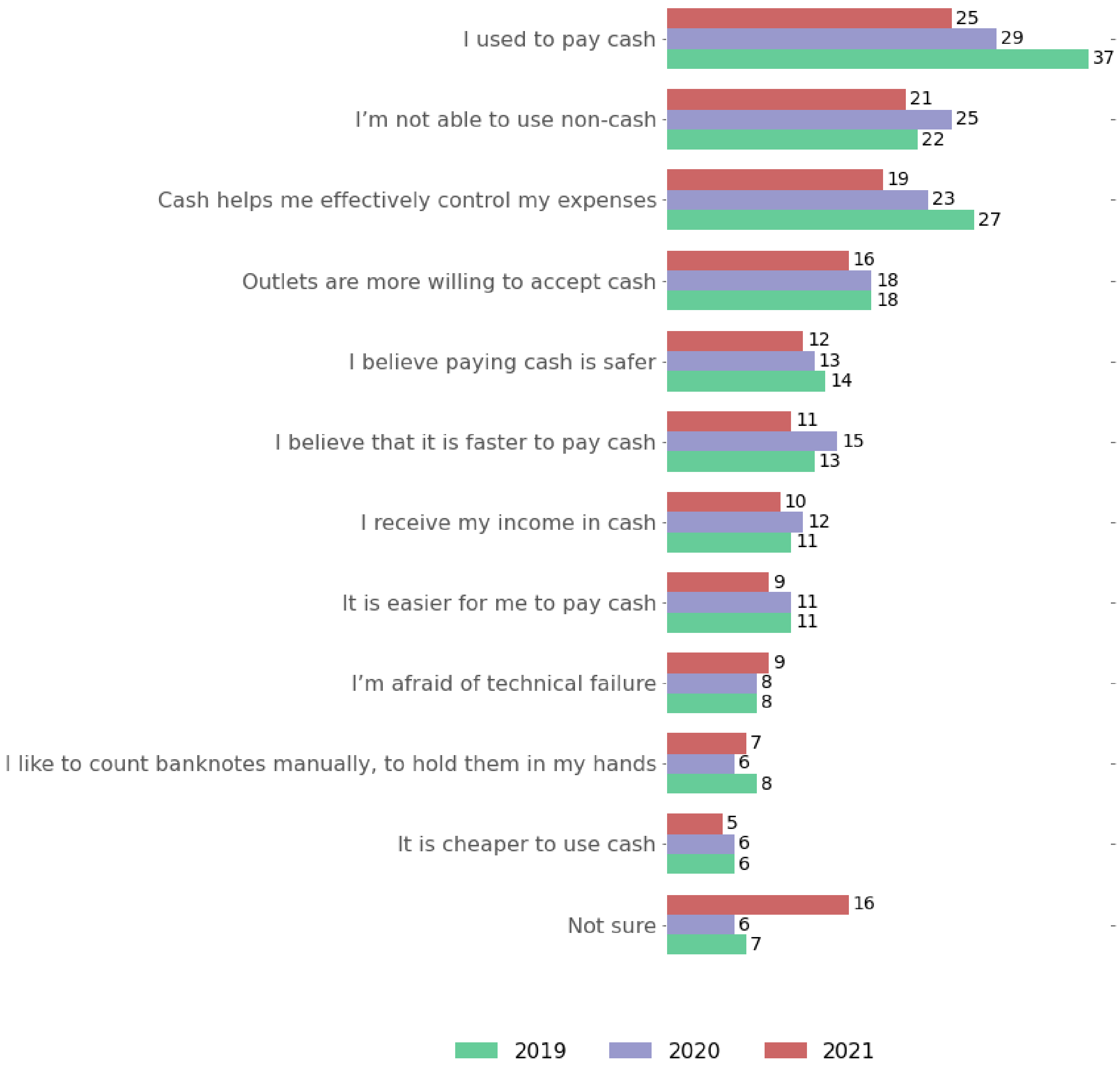


Figure A7. Why do you use a bank card as a payment method?

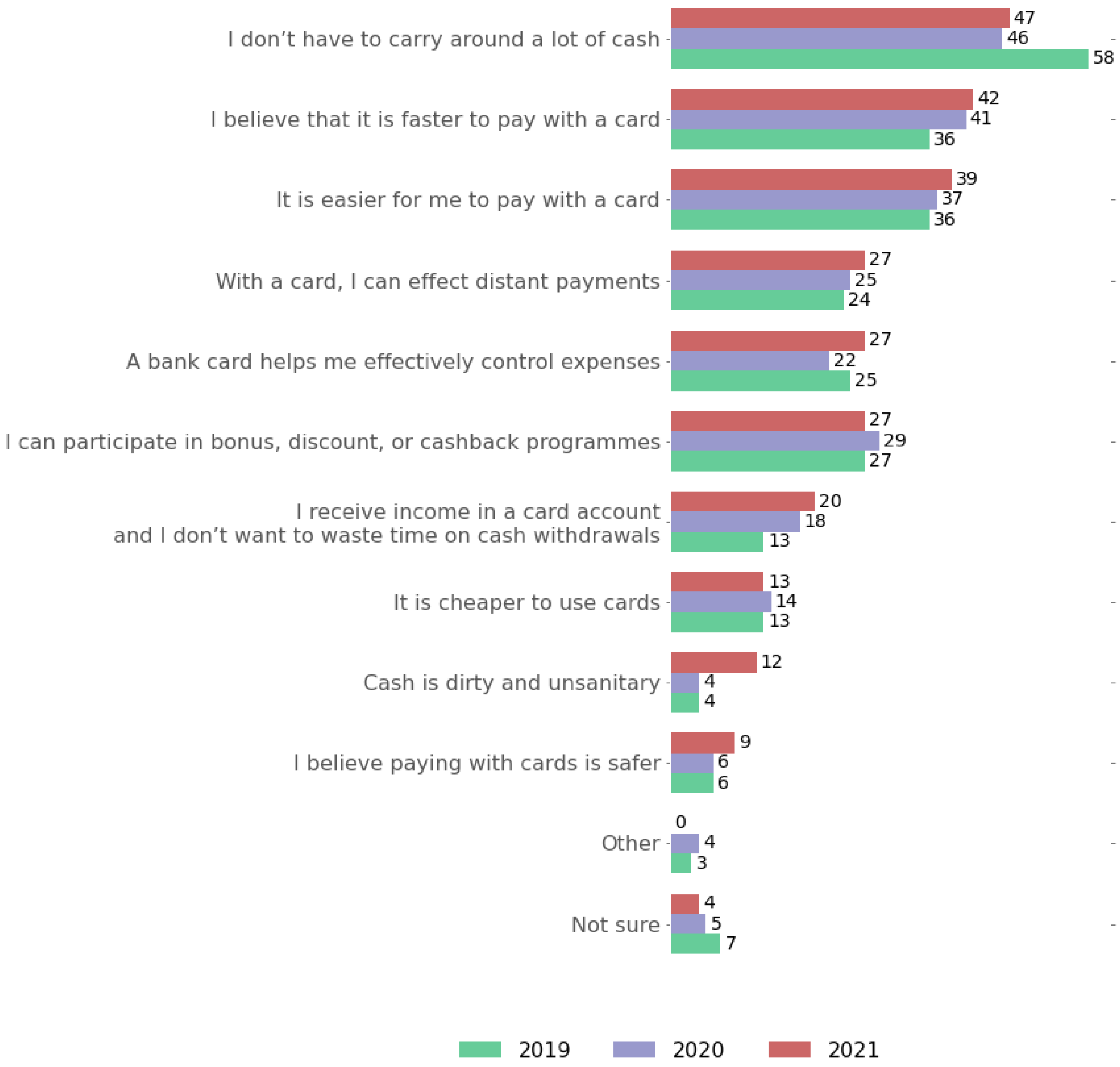


Figure A8. Distribution by age[20]

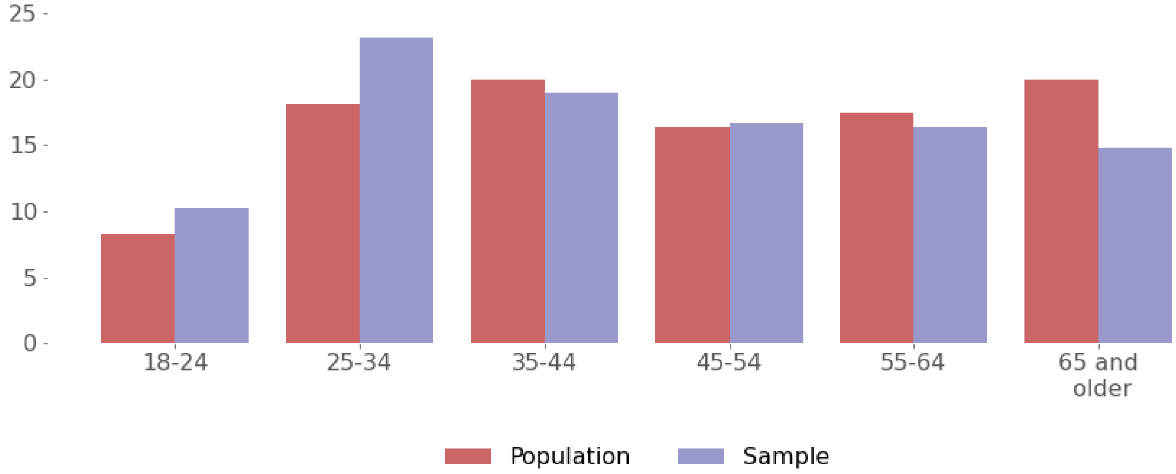


Figure A9. Distribution by city type

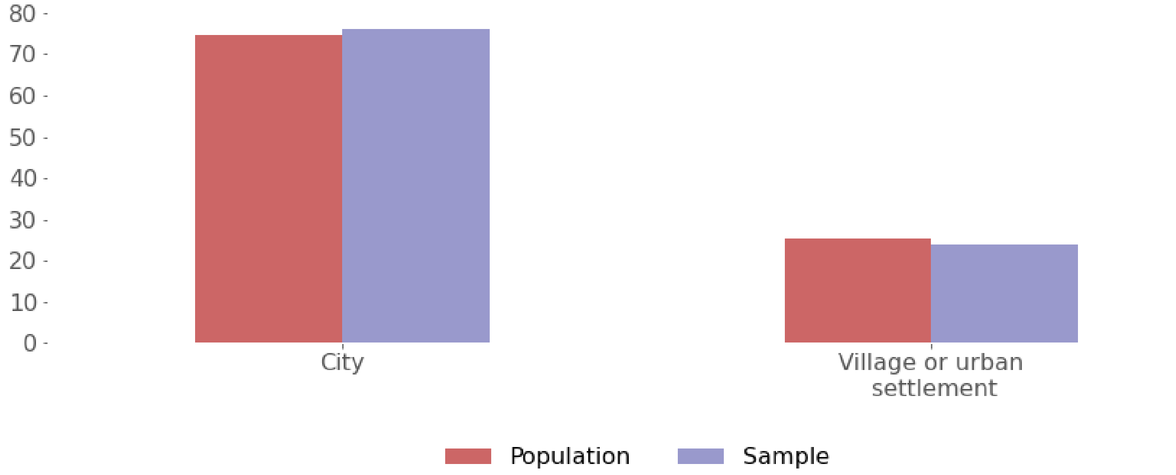
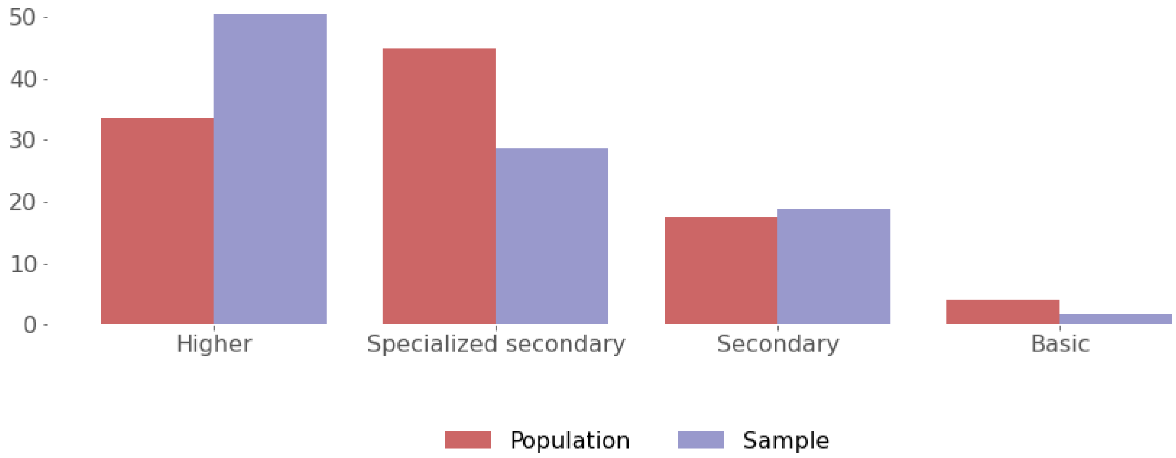


Figure A10. Distribution by education



[20] Persons under 18 are not included in the estimation of shares.

Figure A11. Distribution by income

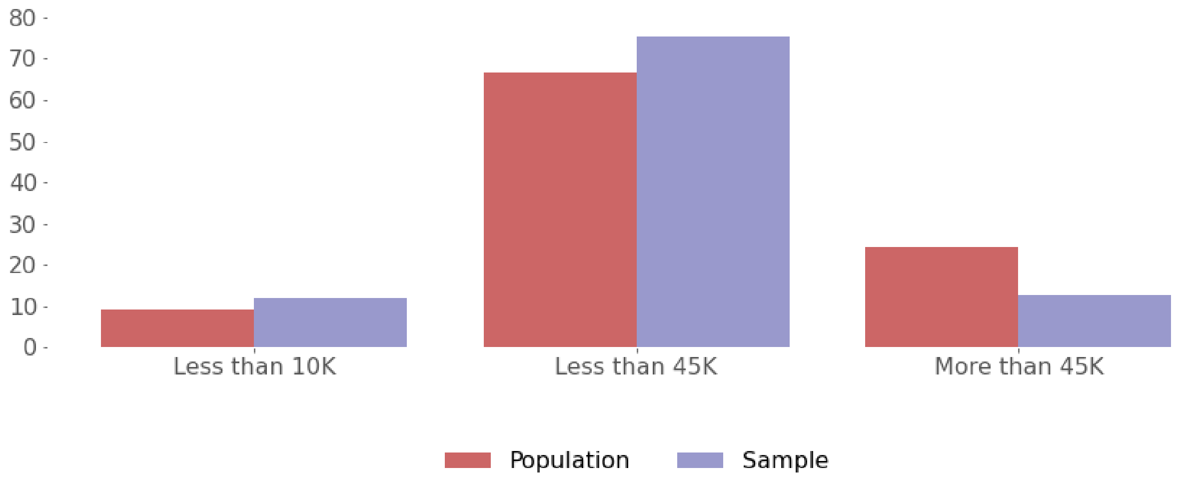


Figure A12. Distribution by employment

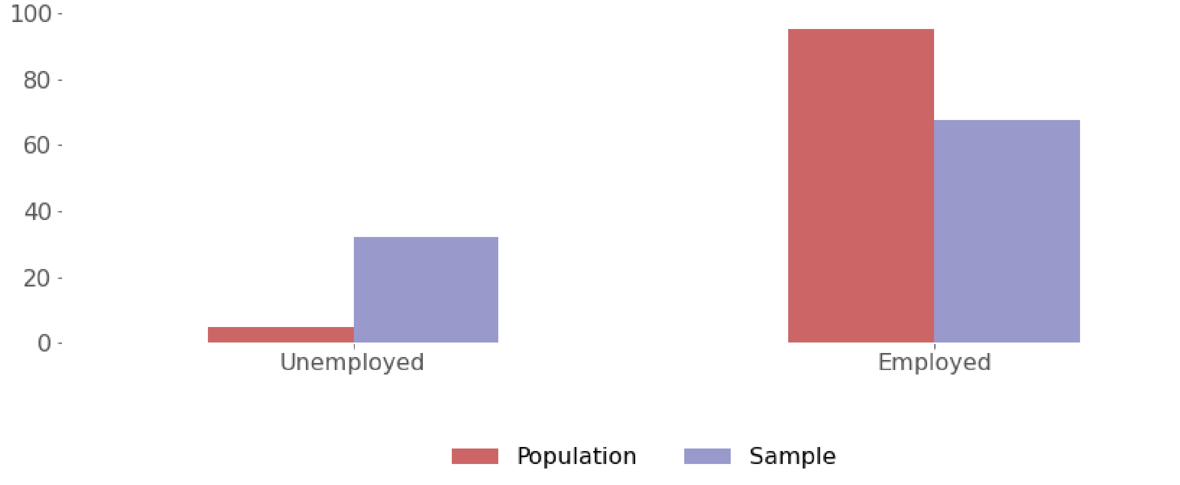


Figure A13. Distribution by region

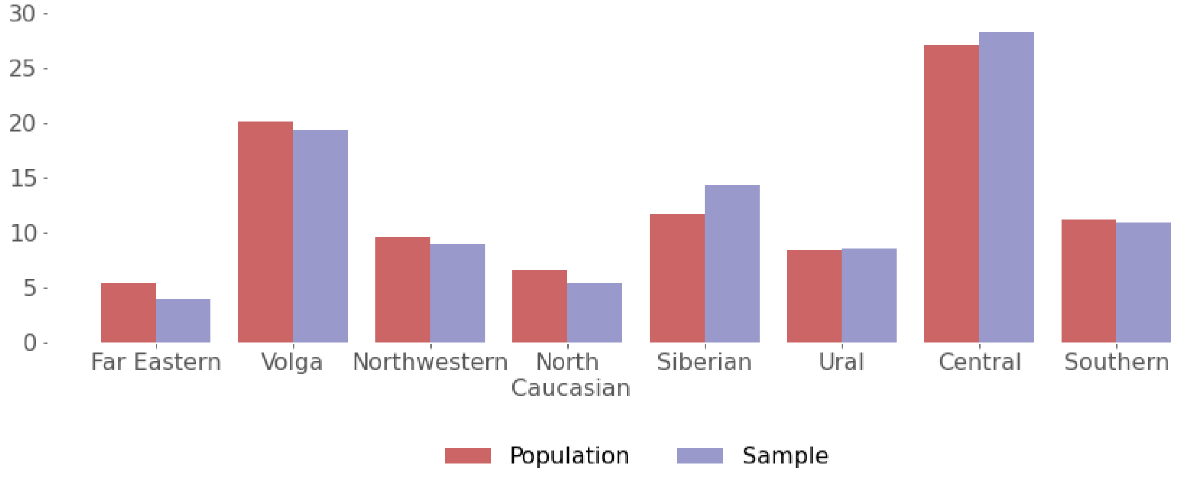


Figure A14. Distribution by sex[21]

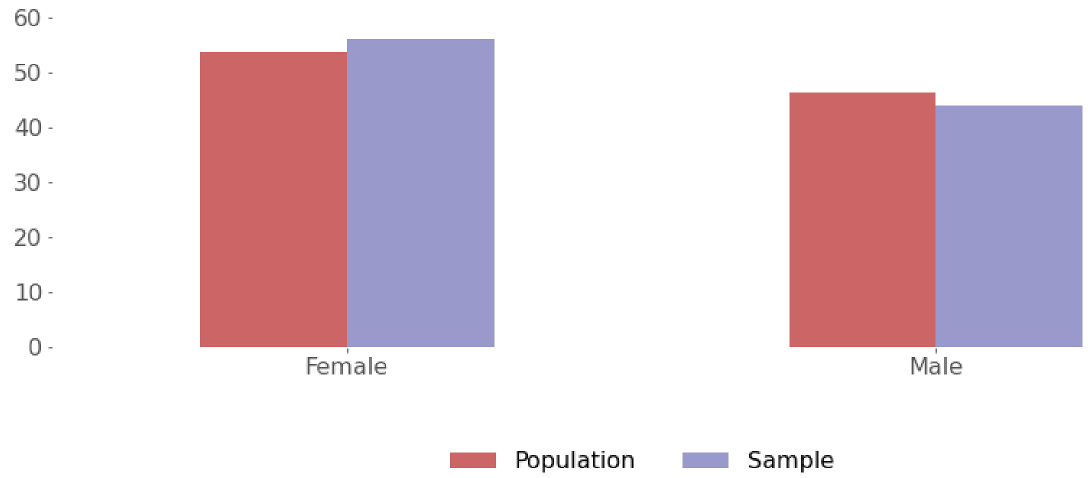


Figure A15. Distribution by age and region

Population **Sample**

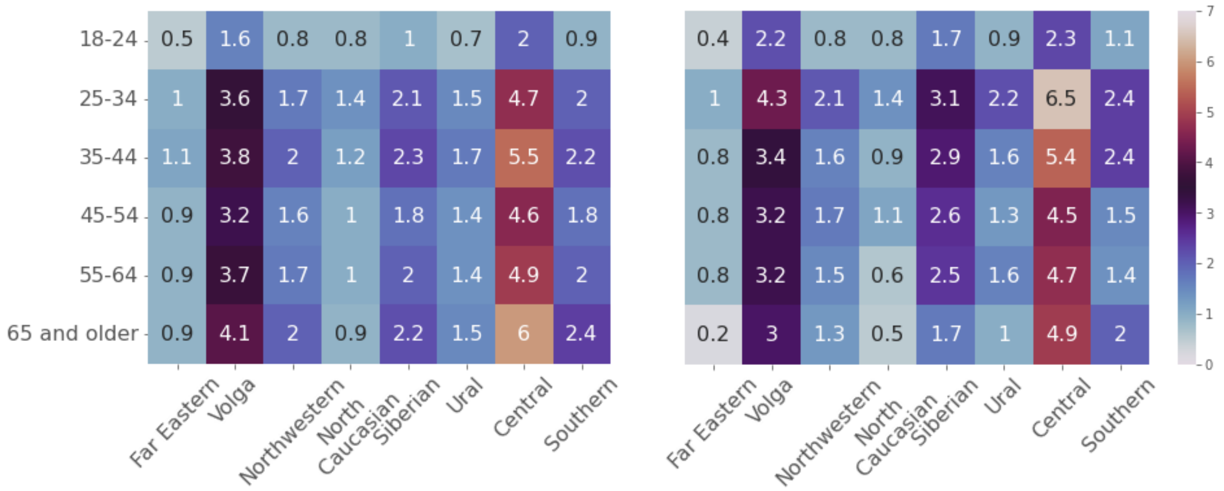


Figure A16. Distribution by age and sex

Population **Sample**

[21] Persons under 18 years old are included.

Figure A17. Distribution by city type and region

Population[22] **Sample**

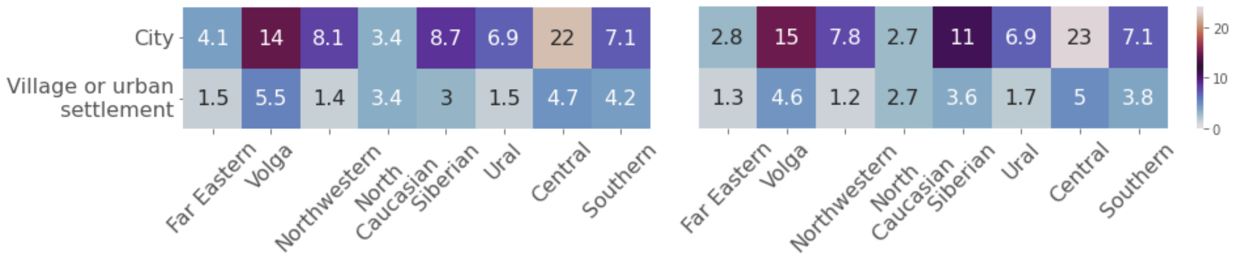


Figure A18. Distribution by sex and region

Population **Sample**

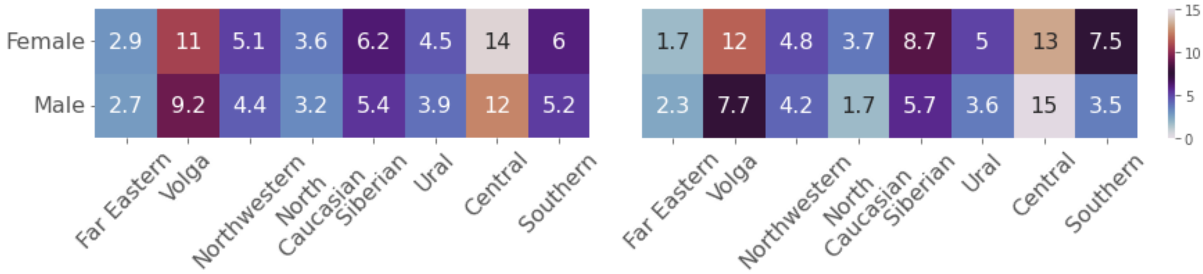
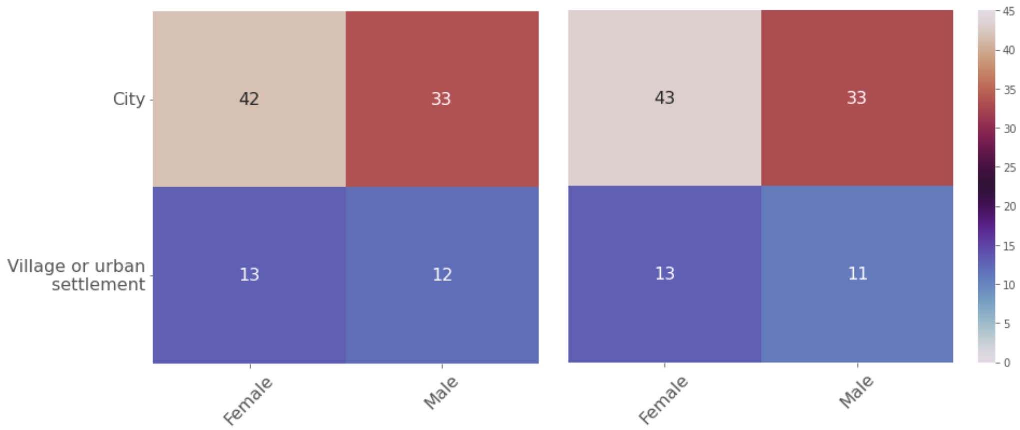


Figure A19. Distribution by city type and sex

Population **Sample**



[22] Persons under 18 years old are included

Appendix 2

Table A6. What are the factors that matter when you choose cash for payments?

Number	Answer	Attribute	Scenario C	Scenario D
1	Cash helps me effectively control expenses	Control of expenses	answers_cash[1]	answers_cash[1]
2	I used to pay cash	Convenience	2*answers_cash[2]	2*answers_cash[2]
3	I believe that it is faster to pay cash	Convenience	answers_cash[3]	answers_cash[3]
4	It is easier for me to pay cash (I don’t have to memorise a PIN, etc.)	Convenience	answers_cash[4]	answers_cash[4]
5	I believe paying cash is safer (I’m afraid of bigger withdrawals from my accounts or the theft of personal data)	Security	answers_cash[5]	answers_cash[5]
6	I like to count banknotes manually, to hold them in my hands	Convenience	answers_cash[6]	answers_cash[6]
7	Outlets are more willing to accept cash	Convenience	answers_cash[7]	2*answers_cash[7]
8	It is cheaper to use cash (I don’t have to pay for servicing cards)	Cost of use	answers_cash[8]	answers_cash[8]
9	I’m afraid of technical failure	Convenience	answers_cash[9]	answers_cash[9]
10	I receive my income in cash	Availability	0.5*answers_cash[10]	0.8*answers_cash[10]
11	I’m not able to use non-cash (please indicate the reason)	Convenience	2*answers_cash[11]	2*answers_cash[11]
12	Not sure	-	-	-

Table A7. What are the factors that matter when you choose bank cards for payments?

Number	Answer	Attribute	Scenario C	Scenario D
1	A bank card helps me effectively control expenses	Control of expenses	answers_card[1]	0.5*answers_card[1]
2	I don’t have to carry around a lot of cash	Convenience	answers_card[2]	answers_card[2]
3	I believe that it is faster to pay with a card	Convenience	0.5*answers_card[3]	0.5*answers_card[3]
4	It is easier for me to pay with a card (I don’t have to count banknotes and coins, etc.)	Convenience	answers_card[4]	answers_card[4]
5	With a card, I can effect distant payments (mobile bank, internet bank)	Convenience	answers_card[5]	0.5*answers_card[5]
6	I believe paying with a card is safer (bank cards are protected better)	Security	answers_card[6]	answers_card[6]
7	I can participate in bonus, discount, and cashback programmes	Cost of use	0	0
8	It is cheaper to use cards (for instance, I get back part of the sum)	Cost of use	2*answers_card[8]+ answers_card[7]	answers_card[8]
9	Cash is dirty and unsanitary	Convenience	answers_card[9]	answers_card[9]
10	I receive income in a card account and I don’t want to waste time on cash withdrawals	Availability	0.5*answers_card[10] + 0.5*answers_cash[10]	0.2*answers_card[10] + 0.2*answers_cash[10]
11	Other (please specify)	Convenience	answers_card[11]	answers_card[11]
12	Not sure	-	-	-

Appendix 3

The model described in Section 4 is linear in terms of scores. However, as noted in Section 6, this assumption may be too restrictive. To relax this assumption, we rewrite the equation for scores as follows:

$$s_n^i = f_i(a_n^i, X_n)$$

where f_i is some function for the $i-$th instrument. It can be a neural network, where coefficients at neurons are the same for all payment instruments, or any other model. Here, for ease of estimation, it is also assumed that the share of the instrument is defined as:

$$sh_n^i = \frac{e^{s_n^i}}{\sum_{j=1}^{N_I} e^{s_n^j}} + \varepsilon_n^i\left(s_n^1, \ldots, s_n^{N_I}\right)$$

where $\varepsilon_n^i\left(s_n^1, \ldots, s_n^{N_I}\right)$ is a random error that depends on the scores. For simplicity[23], we also make the assumption that transaction shares can be rewritten as:

$$sh_n^i = \frac{e^{s_n^i - s_n^1}}{1 + \sum_{j=2}^{N_I} e^{s_n^j - s_n^1}} + \varepsilon_n^i\left(s_n^1, \ldots, s_n^{N_I}\right) = \frac{e^{f\left(a_n^i - a_n^1\right)}}{1 + \sum_{j=2}^{N_I} e^{f\left(a_n^j - a_n^1\right)}} + \varepsilon_n^i\left(s_n^1, \ldots, s_n^{N_I}\right)$$

In the case of two instruments in the estimation stage, as suggested in this article, the function f can be estimated using a random forest model.

[23] The assumption can easily be weakened and does not greatly affect the robustness result.