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Transactional demand for central bank digital currency

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Abstract

We shed light on the demand for a central bank digital currency (CBDC) as a means of payment, based on survey payment data. We provide a quantitative framework to assess transactional demand for CBDC at the point of sale, accommodating a wide range of design choices. We develop a structural model of payment means adoption and usage and estimate CBDC demand based on individuals' preferences for payment method attributes. We disentangle the friction potentially associated to CBDC adoption, assessing two of its potential drivers: information frictions and gradual diffusion of digital payment methods. We find that modelling adoption is key to understanding CBDC demand. Finally, we show that optimal CBDC design, information campaigns, and network effects can substantially boost demand.

Keywords: CBDC; Money demand; Payments; Structural model; Random utility

JEL classification: E41, E42, E47

Non-technical summary

In response to digitalization and the declining use of cash, the economy is undergoing the gradual replacement of public money (cash) with private means of payment in transactions. Recently, such concerns have led central banks to investigate the potential launch of a Central Bank Digital Currency (CBDC). The introduction of a CBDC can lead to two possible scenarios: (1) 'too little' consumer demand for CBDC may lead private digital means of payments to become the dominant medium of exchange; (2) 'too much' consumer demand may lead to bank disintermediation and financial instability. While the 'too much' scenario has been investigated thoroughly in the literature, the 'too little' scenario has received less attention.

In this paper we investigate the 'too little' scenario. We use survey data on payment behaviour and preferences and provide a quantitative framework to assess demand for CBDC as a means of payment at the point of sale, accommodating a wide range of CBDC design choices. We develop a model of payment means adoption and usage and estimate CBDC demand based on how people value different payment method attributes. This model allows to disentangle the cost associated with the adoption of new means of payments, such as a CBDC, and to assess two of its potential drivers of the cost of adopting CBDC: information frictions and gradual diffusion of digital payment methods.

Our results indicate that the adoption rate and market share for CBDC can be increased if CBDC is optimally designed by fine-tuning the attributes (thus increasing the benefits for consumers) and leveraging the drivers of the adoption cost (thus reducing the cost for consumers). We show that the optimal design combines features of cards (transaction speed, ease of use, safety and convenience) and cash (acceptance, anonymity, settlement speed and usefulness for budgeting). Combining the best features of both instruments, CBDC adoption and usage can be boosted substantially. Also, we provide causal evidence that a targeted information campaign can lower the cost of adopting CBDC and thus increase its adoption. Finally, we show that in an environment conducive to the diffusion of mobile applications, network effects may substantially increase CBDC adoption and usage, too.

1 Introduction

The rise of the digital economy coupled with the declining use of cash in transactions have led to a significant shift: the transition from the use of public money to private means of payment in transactions. Since cash is currently the only form of public money available to consumers, the increase in digital payments has led to the decreasing reliance in public money. This development presents a critical question: What potential dangers emerge from a weakened transactional demand for cash, or more generally, central bank money?

Discussions about the risks of a completely cashless economy can be traced back, even in an embryonic form, to the work of Wicksell (1936), who inquires whether banks in a 'pure credit' system could control price fluctuations through a uniform interest rate policy. Related discussions have periodically resurfaced, suggesting that the price level in a cashless world could become indeterminate and render monetary policy irrelevant (Black (1987)), or that payment innovations could potentially undermine the central bank influence over money supply, interest rates, price levels, and economic activity (King (1999), Friedman (1999)).

Despite arguments against the importance of these potential risks (Goodhart (2000), Woodford (2000), Doepke & Schneider (2017)), similar concerns have recently motivated central banks to contemplate the introduction of a Central Bank Digital Currency (CBDC). For example, one of the main motivations to introduce a CBDC is to preserve public money as the anchor of the monetary system (Bindseil *et al.* (2021), Brunnermeier & Landau (2022)). Similarly, a recent survey of 86 central banks conducted by the Bank for International Settlements reveals that improving domestic payment efficiency and safety are the primary motivations for issuing a retail CBDC in 2022. In contrast, the importance of financial stability and monetary policy as motivating factors has declined over time (Kosse & Mattei (2023)).

Addressing the increased interest in the payment function of central bank money requires tackling two crucial questions with respect to CBDC: What characteristics should a CBDC exhibit to be adopted and used for transactions? What policies can a central bank implement to achieve specific adoption and usage shares of CBDC? These questions have been understudied in the empirical literature. As Ahnert *et al.* (2023b) indicate, the current literature focuses on the 'too much' problem, where CBDC is broadly demanded primarily for store-of-value purposes,

potentially disintermediating banks by partly replacing the role of bank deposits. The 'too little' problem, i.e. whether a CBDC is not adopted nor used by consumers, hence hindering its role as a medium of exchange, has received considerably less attention (see survey of literature in Zamora-Pérez *et al.* (2022)). Despite previous efforts to understand demand, there is a notable lack of quantitative research directly addressing this issue. While qualitative studies and discussion papers (for example, Kantar Public (2022) and Bofinger & Haas (2021)) have engaged with the problem, many papers examining the implications of CBDC rely on assumptions of demand levels through calibration or scenario analyses (for example, Andolfatto (2020) and Adalid *et al.* (2022)), sidestepping the challenge of explicitly modelling adoption. Studies modelling CBDC have shed light on understanding demand, but they either abstract from the aspect of adoption (Li (2022)) or do not focus on adoption frictions affecting new means of payments (Huynh *et al.* (2020)). Therefore, insights into this area could significantly enrich our understanding of CBDC demand, as well as inform research on broader macroeconomic implications that hinge on these demand levels.

To answer these questions, we study the potential transactional demand for CBDC at the point of sale by using cross-country data from 17 euro-area countries from the 2022 edition of the "Study on Payment Attitudes of Consumers in the Euro area" (henceforth, SPACE 2022) (ECB (2022a)). We use a structural random utility model of adoption and usage of means of payments to simulate the introduction of a CBDC. Based on heterogeneous consumers' preferences for different attributes of existing means of payments, we characterise CBDC as a set of payment method attributes, such as ease of use, transaction speed, settlement speed, safety, privacy or anonymity, expense awareness or usefulness for budgeting, perceived acceptance, and logistical convenience. By varying the similarity of these attributes to those of either cash or cards, we provide a flexible framework to analyse a multiplicity of different CBDC design choices.

We proceed as follows. First, we study the usage choice to explore the interaction of CBDC with cash and cards, the most well-established means of payments at the POS in the euro area, under the assumption of universal adoption, which is unrealistic but standard in the literature. Then we challenge this standard assumption by demonstrating the need of relaxing it to get realistic demand estimates. To do this, we analyze usage as a function of the adoption rate,

showing that usage levels are heavily driven by adoption rates. Hence, we model the adoption stage, defined as the process in which consumers opt to add new means of payments to their wallet. Unlike the previous literature, we investigate the 'too little' problem by estimating the cost of adopting new means of payment with gradual diffusion and still low adoption rate, exemplified by mobile payment applications. Using the estimated adoption cost, we assess the potential adoption cost associated to a CBDC.

We show that the estimated demand for CBDC is highly sensitive to the adoption cost of novel payment methods, implying that the adoption cost could significantly constrain its transactional demand. However, we also show that an optimally designed CBDC could significantly increase demand. A boost to CBDC demand could be achieved by (1) fine-tuning the payment method attributes of CBDC (thus increasing utility of consumers) and (2) leveraging the drivers of the adoption cost (thus reducing cost of adopting CBDC). In particular, we show that CBDC adoption may be boosted by an information campaign by the central bank and by targeting environments where emergent payment technologies are flourishing.

Our paper adds to the literature in (at least) four ways. First, we provide for the first time a quantitative framework to assess transactional demand for CBDC at the POS in a multiple-country setting by accommodating a wide range of plausible design choices. Second, we model CBDC adoption (how consumers opt to add CBDC to their wallet) as an addition to the 'bundle' of available payment means by explicitly disentangling the cost associated with the adoption of novel means of payment. In this way, we are able to independently estimate the adoption cost of emergent payment technologies (e.g., mobile applications), which is crucial to understanding the potential barriers to CBDC adoption. Third, contrary to previous attempts to model demand, we use data on mobile applications rather than card ownership to identify consumers who may be willing to adopt CBDC. Cards represent a mature technology, with widespread acceptance and usage. The adoption dynamics for such a well-established technology is fundamentally different from those of newly introduced payment methods. Instead, mobile applications offer a better benchmark for the adoption propensity of CBDC. Finally, we assess two potential drivers of the cost of adopting CBDC: information frictions and gradual diffusion of digital payment methods. We provide insights on how central banks might leverage these drivers to facilitate

CBDC adoption.

Our study contributes to the emerging empirical literature on CBDC demand, where existing contributions remain limited, with a few notable exceptions such as Huynh *et al.* (2020), Bijlsma *et al.* (2021), Li (2022), Abramova *et al.* (2022), and Gross & Letizia (2023)[1]. Our approach builds upon Huynh *et al.* (2020), who model payment instruments demand for transactions through adoption and usage. However, we diverge from their study in two key aspects. We offer an explicit decomposition of the cost associated with the adoption of different means of payment, which is particularly valuable as it allows to estimate the adoption cost of emergent payment technologies (e.g., mobile applications) to understand the potential barriers to CBDC adoption. Also, we propose a new proxy for the adoption propensity of a novel means of payment, such as CBDC, based on self-reported preferences for mobile applications. We argue that the adoption propensity of CBDC cannot be adequately proxied by the availability or ownership of a mature and widely adopted means of payment, such as cards. Unlike Li (2022), we decouple transactional and store-of-value demand for CBDC, thus disentangling decisions on how to pay from broader asset allocation considerations between cash and deposit holdings.[2] As the determinants for transactional and store-of-value functions do not fully overlap, we focus on the determinants influencing transactional demand. Finally, our approach to characterise a CBDC relies entirely on consumer-reported preferences for payment attributes, avoiding the potential comparability issues associated with composite indicators that use diverse sources.

The rest of the paper is structured as follows. Section 2 introduces the model for the usage decision under both universal adoption and conditioned on adoption. Section 3 describes the data. Section 4 reports the usage model estimates. Section 5 shows how to simulate CBDC and how its usage strongly varies with the adoption rate. Given this finding, Section 6 relaxes the universal adoption assumption by introducing the model for the adoption decision and studying potential drivers of the adoption cost. Section 7 concludes. Finally, the Appendix provides more

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[1] Most of the literature on CBDC focus on financial stability and monetary policy transmission, e.g. Agur *et al.* (2022), Keister & Sanches (2023), Keister & Monnet (2022), Ferrari Minesso *et al.* (2022), Whited *et al.* (2022), Fernandez-Villaverde *et al.* (2021), Schilling *et al.* (2020), Kahn *et al.* (2022), Bordo & Levin (2017), Davoodalhosseini (2022), Assenmacher & Krogstrup (2021), Chen & Siklos (2022), Barrdear & Kumhof (2022), Williamson (2022a), Williamson (2022b), Meaning *et al.* (2021), Castren *et al.* (2022), Ramadiah *et al.* (2021), Munoz & Soons (2023), Ahnert *et al.* (2023a), Fegatelli (2022), Zellweger-Gutknecht *et al.* (2021), Burlon *et al.* (2023), and Kahn (2020).

[2] See estimates of both components for euro cash demand in Zamora-Pérez (2021).

details on models, results and data.

2 Model for usage decision

In this section, we develop a random utility model to examine the choices consumers make when using mature means of payments, i.e. cash and cards, in point-of-sale (POS) transactions under the assumption of universal adoption and acceptance. In section 4 we provide the model estimates, and in section 5 we use this model to simulate the introduction of a CBDC and predict its potential capture of usage transaction share from these mature means of payment, contingent on various designs. For this initial model, we deliberately exclude the impact of CBDC on legacy (e.g., bank cheques) and innovative (e.g., mobile payments) means of payment, which are not widely used in the euro area.[3] The details of the model are reported in Appendix A, while the essential elements are reported below.

2.1 Usage decision model with universal adoption and acceptance

Each consumer $i \in \{1, \ldots, I\}$ is faced with the choice of a specific means of payment $j \in \mathcal{J}$ to use in a transaction $l \in \{1, \ldots, L\}$, where I and L are the number of consumers and transactions and $\mathcal{J}$ is the set of payment instruments. We make the assumption of universal adoption and acceptance, which will be subsequently relaxed, i.e. all means of payments are (i) adopted by consumers; (ii) accepted by merchants. The utility that consumer i gains from transacting with means of payment j depends on the preferences towards the means of payments' attributes, consumer i's socio-demographic characteristics and transaction l's features. The utility gained from transacting with j can be written as

$$u_{i,l,j} = v_{i,l,j} + \epsilon_{i,l,j} \tag{1}$$

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[3]According to the SPACE 2022 survey, at present, cash and cards represent the most commonly used means of payment at the POS in the euro area. Specifically, cash constitutes 59% of these transactions, while card payments contributed to 34% of POS transactions (these aggregate figures include Germany and the Netherlands, which are not present in the data used in this paper, as their respective central banks conducted separate surveys). When evaluated in terms of transaction value, the dynamics differ, with card payments (46%) slightly outpacing cash payments (42%).) The remaining transactions are accounted for by a wide variety of payment instruments such as bank cheques, all modalities of mobile payment apps, credit transfers, loyalty points, vouchers and gift cards such as Amazon or iTunes gift cards, and other payment instruments.

where $v_{i,l,j}$ is the observed usage utility and $\epsilon_{i,l,j}$ is an utility shock embedding unobserved preferences. We assume that (i) the usage utility $v_{i,l,j}$ is linear, i.e. $v_{i,l,j} = \alpha' \mathbf{x}_{i,j} + \eta_j + \gamma_j' \mathbf{z}_{i,l}$, where α is a preference parameter for the attributes of a means of payment, η_j is a constant specific to a means of payment proxying the unobserved (left out from the survey) attributes and γ_j is a means-of-payment-specific parameter summarizing the effect of consumer-transaction characteristics, $\mathbf{z}_{i,l}$; and that (ii) the preference parameter α is homogeneous across consumers.

Consumer i chooses instrument j with higher probability if $u_{i,l,j} > u_{i,l,k}$, where k is a means of payment other than j. Due to the unobserved utility shock, even if the usage utility from transacting with k is higher than the one from transacting with j, instrument j may be chosen if its associated utility shock can sufficiently compensate. Assuming that the utility shock $\epsilon_{i,l,j}$ follows a standard Gumbel or type I extreme value distribution, i.e. $\epsilon_{i,l,j} \overset{i.i.d.}{\sim} Gumbel(0,1)$, and considering a binary model with two means of payment in the choice set $\mathcal{J}$, i.e. cash and cards (debit or credit), i.e. $j \in \{cash, card\}$, the probability that consumer i chooses means of payment j is given by

$$\mathbb{P}_{i,l,j} = \frac{e^{v_{i,l,j}}}{e^{v_{i,l,cash}} + e^{v_{i,l,card}}} \tag{2}$$

As the utility $v_{i,l,j}$ increases, the probability of choosing means of payment j increases, too. In the limit, if $v_{i,l,j} \to \infty$ then $\mathbb{P}_{i,l,j} \to 1$, while if $v_{i,l,j} \to -\infty$ then $\mathbb{P}_{i,l,j} \to 0$.

$$ln\left(\frac{\mathbb{P}_{i,l,card}}{\mathbb{P}_{i,l,cash}}\right) = \alpha'(\mathbf{x}_{i,card} - \mathbf{x}_{i,cash}) + \eta_{card} + \gamma_{card}' \mathbf{z}_{i,l} \tag{3}$$

The estimated parameters represent effects on the log-odds ratio.

2.2   Conditioning usage on adoption and acceptance

So far the model assumes that cash and cards are always adopted by consumers and accepted by merchants. Now, we relax this assumption by conditioning the usage probability on consumer adoption and merchant acceptance as follows:

$$\mathbb{P}_{i,l,j|*} = \begin{cases} \mathbb{P}_{i,l,j} & j,k \in * \\ 1 & j \in * \ \& \ k \notin * \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

where * represents a bundle of payment instruments usable at the POS. If a means of payment is not adopted by a consumer, then she cannot use it at the POS. Hence, usage of a payment instrument at the POS is constrained by the adoption choice of a consumer. Let $* = b \in \mathcal{B}$ be a bundle of payment instruments from the choice set $\mathcal{J}$ which is adopted by a consumer, where $\mathcal{B}$ is the set of all possible collections of means of payments. For example, $b \in \{card, cash\}$ means that a consumer adopts a card in addition to cash. Estimation is identical, but now $\mathbb{P}_{i,l,j|b}$ replaces $\mathbb{P}_{i,l,j}$. This way, we condition on consumer adoption, which is taken exogenously. However, adoption is endogenous and in subsection 5.2.1. we show the need to investigate the determinants of the adoption decision. In section 6 we model explicitly this decision.

Secondly, the survey records acceptance of a payment instrument as perceived by consumers (questions QA8Al and QA8AIl, Appendix C). The two-sidedness of the payment market makes it important to take into account merchant acceptance. If a means of payment is not accepted by a merchant, the consumer cannot use it at the POS. Hence, usage of a payment instrument may be induced by merchant acceptance rather than being a choice based on consumer preferences. Let $* = f \in \mathcal{B}$ be a bundle of payment instruments from the choice set $\mathcal{J}$ which is accepted by a merchant. For example, $f \in \{card\}$ means that a firm accepts only cards (and not cash). .[4] As in Wakamori & Welte (2017), we additionally condition the usage probability on observed merchant acceptance from consumer responses, i.e. we take $* = b \cap f$. Estimation is identical, but now $\mathbb{P}_{i,l,j|b \cap f}$ replaces $\mathbb{P}_{i,l,j}$.

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[4]Here we take the responses given by consumers as a proxy for merchant acceptance. A promising alternative may be to take merchant acceptance rates from merchants directly. We compare perceived acceptance with a representative survey of the payment preferences and acceptance of euro-area companies conducted by the ECB. Aggregate results suggest that consumers' perceived acceptance is a good proxy for actual acceptance. See ECB (2022b)). Either way, we may use merchant characteristics to model the acceptance decision as well. For example, acceptance may depend on the merchant sector, turnover, number of employees, interchange fees etc. We leave this extension for future research, as it requires information not currently available in the SPACE survey.

3   Data

We use SPACE 2022 payment diary's transaction-level data on payment behaviour and consumer-level data on consumer preferences for different attributes of cash and cards. In this data, each row represents a transaction and for each transaction a consumer can use only one means of payment. The survey design, sample size, representativeness, treatment of non-responses, imputations and weighting scheme, selected questions and summary statistics are reported in more detail in Appendix C.

3.1   Usage decision

As response variable we consider the usage decision revealed by consumers through their card and cash transactions. Whenever a consumer carries out transactions with a card her usage decision takes value 1, while whenever she carries out a transaction in cash her usage decision takes value 0. We consider up to eight POS transactions[5] carried out by each consumer in cash or with a card in a one-day window. As the usage decision depends on the merchant acceptance in each payment situation, we use also use data on what means of payments were accepted in each transaction.[6]

3.2   Payment instrument attributes

We use SPACE 2022 data to extract the payment instrument attribute preferences, $\mathbf{x}_{i,j}$. Participants in the survey are asked to identify the main advantages of using cash over cards, and *vice versa*, along eight main attributes: 'Perceived acceptance', 'Transaction speed', 'Ease of use', 'Safety', 'Budgeting', 'Anonymity/Privacy', 'Settlement speed' and 'Convenience'.[7] Summary statistics about the payment method attributes are presented in table 6 of Appendix C5.

Out of the eight attributes, consumers select up to three key advantages for both payment instruments (cash and cards). For the chosen attributes we assign a value of 1 and for the not-chosen attributes a value of 0. The survey considers five attributes for both payment instruments

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[5]We exclude Person-to-Person (P2P) payments.

[6]The relevant question for usage, reported in Appendix C, is QA7Al ('How did you make the lth payment?'). The relevant questions for acceptance are QA8Al and QA8AIl.

[7]For brevity, these are the names we attach to the attributes. The complete survey questions (QQ13a and QQ13b) are reported in Appendix C6.

('Perceived acceptance', 'Transaction speed', 'Ease of use', 'Safety', and 'Budgeting' - a term used here to summarise the attribute of aiding consumer expense awareness). However, three attributes are uniquely exhibited by a single payment instrument: the benefit associated with not carrying cash ('Convenience', for brevity) is only applicable to cards while 'Anonymity/Privacy' and instant settlement speed (or simply 'Settlement speed') are exclusively applicable to cash.[8]

As an example, consider the preference profile of an hypothetical consumer: consumer i. Suppose consumer i identifies 'Transaction speed' and 'Convenience' as the two main benefits of using cards (she reports only two main advantages for cards). Then, we assign value 1 to these attributes in her preference profile for cards. For cash, she chooses 'Anonymity/Privacy', 'Ease of use', and 'Budgeting', denoted as 1 in her cash preference profile. Attributes 'Perceived acceptance', 'Safety', and 'Settlement speed' are not identified as advantages for either cards or cash, hence are recorded as 0 in both preference profiles[9]. As with consumer i, each consumer's preference profile, i.e. a combination of '1's and '0's for both cards and cash, offers individual-level information into the perceived advantages of cash and cards. This information is integral to modeling consumer decisions and predicting shifts in transaction behavior in the face of a new payment option, such as CBDC.

Our approach in capturing consumer preferences presents important strengths with respect to other approaches (e.g. Li (2022)). First, it is free from the assumptions inherent to composite attributes, which incorporate supplemental information and may introduce assumptions and comparability issues. For example, our attributes are designed to be always instrument-specific, i.e. they capture consumer preferences distinctly for each payment method. This approach contrasts with, e.g., Li (2022), where some attributes, such as anonymity and budgeting usefulness, reflect general consumer preferences, but do not specify the consumer's perceived advantage for a particular payment instrument. Second, our approach is less vulnerable to scale use bias (some

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[8]In contrast, Li (2022) considers budgeting as a feature unique to cash, while we allow it to be a potential advantage associated with card use as well. Furthermore, we consider that cash holds an advantage in terms of settlement speed relative to cards, as cash allows instantaneous settlement.

[9]For some consumers, some preferences could be unidentified as consumers could assign value '1' along the same attribute for both cards and cash. Although the prevalence of these unidentified cases is low (ranging from 0 to 5% of consumers across the different attributes), assigning value 1 to both questions does not need to be inconsistent. Consumer i may value perceived acceptance for all means of payments (for low value payments she values cash acceptance and for high value payments she values card acceptance). In what follows, these instances, which do not provide a distinct preference towards cash or cards, are taken into account. Eventually, what matters for consumer choice is the comparison embedded in equation 3.

respondents may be susceptible to select extreme cases of Likert scales) and does not require related data standardization which may introduce bias or additional assumptions.[10]

3.3 Consumer- and transaction-level characteristics

In the 'Preliminary results' section, we consider a set of socio-demographic variables that capture the essential attributes of the consumer (consumer-level characteristics). These include income category and education level, gender, age band, rurality (the size of the locality where the consumer resides), and occupation. As we detail in Appendix C5, payment behaviour at the POS varies across sociodemographic groups, with cash remaining the dominant choice across all groups, but more so for older, lower-income, and less-educated individuals, and *vice versa* for the use of card payments. For a more detailed description, see table 7 and Figure 11 which show the average share of transactions for different means of payments (including mobile apps and other legacy and innovative payments included in the category of 'Other'). Another consumer-level characteristic is the cash balance.[11] Cash balance contributes to understanding the payment choice dynamic, as higher cash balances are associated with higher cash usage (see Figure 15).

The transaction-level characteristics, e.g. the payment location and transaction size, also serve as explanatory variables in our preliminary analysis. The transaction location encompasses a diverse range of establishments, e.g. supermarkets, shops, and restaurants, providing information on context-specific payment choice. Figure 13 in Appendix C5 depicts the different means-of-payments usage rates in selected locations. Transaction size, indicating the monetary value of the purchase, captures how the payment choice varies with differing transaction values.

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[10]Despite their advantages, our attributes have limitations, although they have a limited impact in our context. First, we cannot gauge the intensity of preferences as we only assign binary information. While we cannot capture weaker or stronger preferences, our interest is to record consumers' overall preference profile between cash and cards for various attributes, rather than the degrees of those preferences. Relatedly, we cannot make intra-consumer comparisons of attribute importance. That is, in the above example, we cannot say that consumer i values 'Anonymity/Privacy', 'Ease of use', and 'Budgeting' equally, as she is not ranking the importance of each attribute but just stating what attributes are more important. Nevertheless, this drawback is innocuous in our setting as we are mainly interested in comparing attributes across (not within) consumers. Finally, we assume that if an attribute is not listed among a consumer's top three, the consumer is indifferent with respect to the remaining attributes. However, about two-thirds of consumers identify between zero to two main attributes for card payments, and over half do the same for cash. This fact suggests that this limitation affects a small part of our sample and does not significantly distort consumer preferences.

[11]The cash carried by consumers at the beginning of the day is consumer-level as it does not vary across transactions, but it is related to the transactions made in the day of the diary (if a consumer has more cash, she tends to pay in cash).

We show in Appendix C5 (Figure 14) that lower transaction sizes are associated with higher cash usage, and *vice versa* for card usage. Further information of these transaction-level variables is elaborated in Appendix C5.

4   Usage model estimates

The usage model is binary, i.e. it considers cash and cards as the two major means of payments available to consumers at the POS. We estimate different models with various controls under universal adoption and acceptance.[12] Table 1 reports the estimated coefficients, i.e. the marginal utilities appearing in the odds ratio.[13] From column (1) to (3) the control set expands to assess the sensitivity of significance, sign and magnitude of the estimates.

All attributes are highly statistical significant with stable sign and magnitude. Preference towards anonymity/privacy, which is up-to-date a feature unique to cash, and settlement speed, which is instantaneous only for cash, reduce the odds of using cards in favour of cash. Preference for cards in terms of (perceived) acceptance, transaction speed, ease of use, safety, logistical convenience and usefulness for budgeting increase the odds of card usage. The 'Card usage benefit' constant is significantly negative. This aligns with the prevalent use of cash in POS transactions, as observed in the summary statistics (see, for example, Table 7 and Figure 11 in Appendix C5). This constant can be interpreted as encapsulating the effect of unobserved attributes not represented in our survey data.

Turning to the model estimates when usage is conditioned on adoption and acceptance (see subsection 2.2), Table 2 reports the main estimates. The first column reports parameter estimates when the usage model is conditioned on adoption, while the second column provides estimates when conditioned both on adoption and acceptance. Coefficients' magnitude changes slightly, but significance remains strong and signs are unchanged. In this table, we use survey

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[12]We carry out the estimation in *R 4.0.3* (Hess & Palma (2019)).

[13]For the attributes unique to just one means of payment, or with restricted domain, we rewrite the odds ratio to have the desired interpretation. For example, in case of anonymity an increase in the regressor $x_{i,card} - x_{i,cash}$ cannot be interpreted as an increase in anonymity, as only $x_{i,cash}$ can take up a positive value ($x_{i,card}$ is zero by design) and, therefore, an increase in $x_{i,card} - x_{i,cash}$ is rather interpretable as an increase in trackability. To have a suitable interpretation we can easily look at $x_{i,cash} - x_{i,card}$ and exploit the identity $\hat{\alpha}(x_{i,card} - x_{i,cash}) = -\hat{\alpha}(x_{i,cash} - x_{i,card})$. In this case, an increase in $x_{i,cash} - x_{i,card}$ is clearly an increase in anonymity. The same reasoning applies to settlement speed.

data on adoption and acceptance. The survey reports ownership of a payment instrument by consumers (question QQ1A, Appendix C), which we use (temporarily) as an indicator of adoption. Consumers report a 94.4% rate of card ownership and cash is assumed to be accessible by everyone[14]. Consumers report an acceptance rate of cards of 83.2% and an acceptance rate of cash of 96.1%.

5   Simulating a central bank digital currency

In this section, we simulate a CBDC employing the usage model. We begin by examining the prevalent assumption of universal adoption within the usage decision model for cash, cards, and CBDCs at the POS in the euro area. In subsection 5.1.1, we simulate the introduction of CBDC under this traditional assumption, providing a baseline for comparison. Subsequently, in subsection 5.1.2, we adjust the model to reflect the same adoption and acceptance rates for CBDC as currently observed for cards. The subsequent sensitivity analysis in subsection 5.2.1. models usage conditional on varying adoption and acceptance levels, further confirming the need to realistically model adoption.

We define CBDC as a collection of payment instrument attributes as perceived by consumers. Different CBDC designs correspond to different arrangements for the payment method attributes. In particular, we introduce a CBDC which shares some common traits with cards and cash. Suppose the central bank issues a CBDC with the following attributes

$$\mathbf{x}_{i,CBDC} = \lambda' \mathbf{x}_{i,card} + (\mathbf{1} - \lambda)' \mathbf{x}_{i,cash} \tag{5}$$

If $\lambda = \mathbf{1}$ the consumer perceives the CBDC exactly as it perceives a card and, therefore, we label it as a card design. If $\lambda = \mathbf{0}$ the consumer perceives the CBDC exactly as it perceives cash and, therefore, we label it as a cash design. When $\lambda \in (\mathbf{0}, \mathbf{1})$ we have a hybrid design. In particular, if $\lambda \in (\mathbf{0.5}, \mathbf{1})$ we have a card-like design, while when $\lambda \in (\mathbf{0}, \mathbf{0.5})$ we have a cash-like design.

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[14]We deem this assumption realistic in euro-area countries based on survey data. SPACE 2022 reports a minority of individuals with stated difficulty of accessing cash. In this paper we abstract from these variations in perceived access to cash

In the first simulation we make the following assumption: once a CBDC is introduced, (i) a CBDC is instantaneously 1) adopted by consumers; 2) accepted by merchants; (ii) the preference parameter $\hat{\alpha}$ is unaltered. We can now compute the usage utility as

$$v_{i,l,CBDC} = \hat{\alpha}'\mathbf{x}_{i,CBDC} + \hat{\eta}_{CBDC} + \hat{\gamma}'_{CBDC}\mathbf{z}_{i,l} \tag{6}$$

where $\hat{\eta}_{CBDC} \in \{0, \hat{\eta}_{card}\}$.[15] The probability of using CBDC for payment is given by

$$\mathbb{P}_{i,l,CBDC} = \frac{e^{v_{i,l,CBDC}}}{e^{v_{i,l,cash}} + e^{v_{i,l,CBDC}} + e^{v_{i,l,card}}} \tag{7}$$

In the next subsection we report results from simulating a CBDC by altering all attributes at once.

5.1 Introduction of a CBDC

Based on equation (5), we introduce a CBDC by simulating different design options as mediated by consumers' preferences. Those translate into different usage utilities and, therefore, usage probabilities. Usage probabilities at the individual level allow to compute a distribution and the aggregate share of CBDC in a payment economy with cash and cards.

5.1.1 Universal adoption and acceptance

A CBDC perceived to be designed as a card (Figure 1, panel (a)) would lead to a usage share of 0.280 for CBDC and usage shares for cash and cards of 0.439 and 0.280, respectively.[16] On the other hand, assuming technological feasibility, a CBDC perceived to be designed as a form of digital cash (panel (b)) would lead to a usage share of 0.371 for CBDC and usage shares for cash and cards of 0.371 and 0.257, respectively. All in all, the introduction of a CBDC perceived exactly identical to one of these two payment instruments leads to an exactly identical choice distribution of CBDC compared to the replicated payment instrument. Moreover, a CBDC perceived to be designed as card or cash tends to compress the choice distribution of the

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[15]In the following simulations, for computational reasons we assume $\hat{\gamma}_{CBDC} = \mathbf{0}$. This assumption is without loss as the coefficients of the payment instrument attributes are robust to the inclusion of additional controls (see Table 1).

[16]In other words, 28% of the transactions would be carried out with CBDC and the rest with cash and cards.

(a) Perceived card design   (b) Perceived cash design
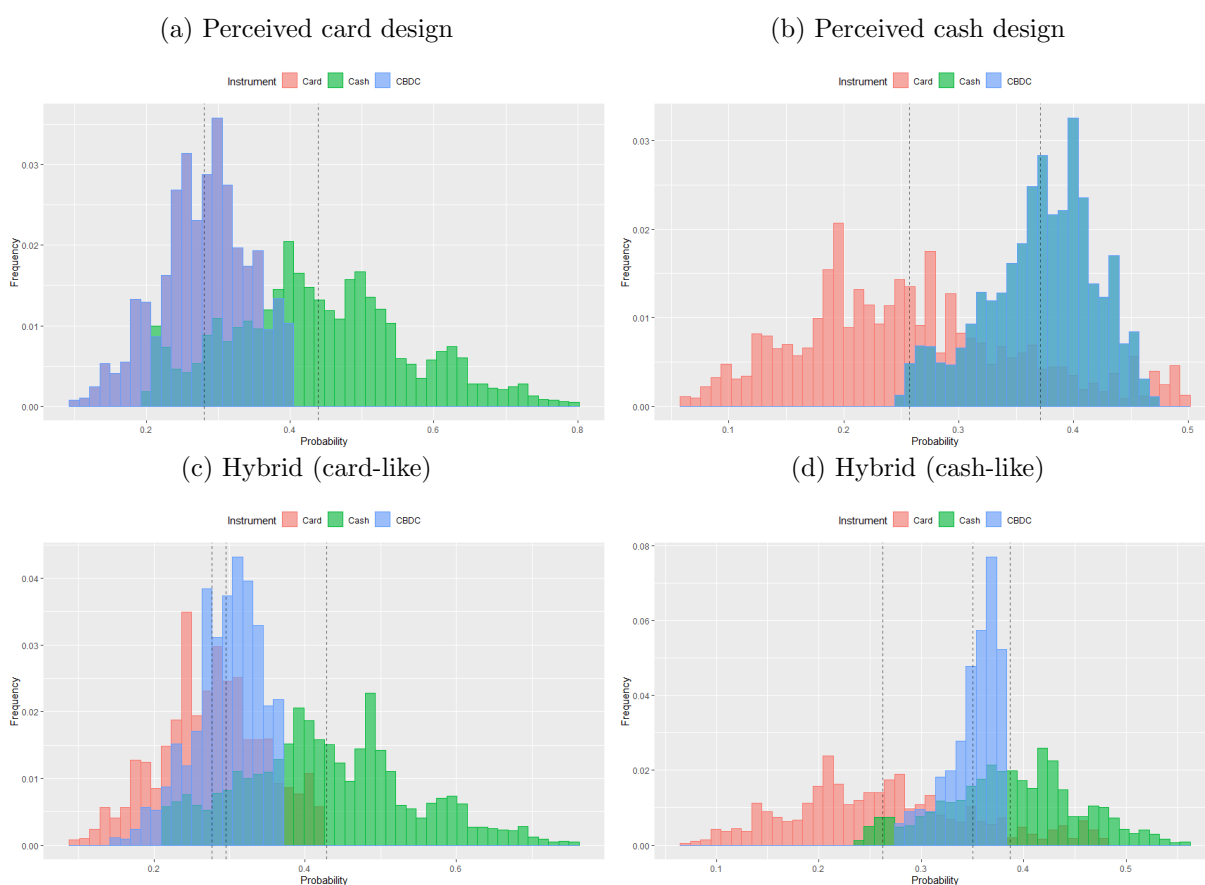
(c) Hybrid (card-like)   (d) Hybrid (cash-like)

Figure 1: CBDC designs perceived to be as card and cash (upper panel) and hybrid (lower panel). Distributions of the usage choice probability for cash (green), cards (red) and CBDC (blue) at the consumer level. Vertical dashed lines represent the mean of these distributions. For each consumer the usage probabilities for cash, cards and CBDC add up to one. The tuning parameter λ is set to 0.8 for the hybrid, card-like design and to 0.2 for the hybrid, cash-like design.

replicated instrument and to spread the choice distribution of the non-replicated instrument.[17]

With $\lambda = 0.8$, i.e when consumers perceive an hybrid design reminding a card, the usage share of CBDC is 0.295 and usage shares of cash and cards are 0.428 and 0.276, respectively. Finally, with $\lambda = 0.2$, i.e. when consumers perceive an hybrid design reminding cash, the usage share of CBDC is 0.350 and usage shares of cash and cards are 0.387 and 0.263, respectively. We expect consumer adoption and merchant acceptance to play a role for CBDC usage and, therefore, investigate this important aspect in the following subsections.

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[17]The two limit cases do not need to provide the lower and upper bound of CBDC usage. In fact, there may be a combination of cash and card characteristics that maximizes CBDC usage and this maximisation can be achieved by fine-tuning λ. We report this exercise in subsection 6.4.1.

5.1.2 Joint adoption and acceptance

We constrain CBDC usage by jointly using information on consumer adoption (in the form of ownership) and merchant acceptance. We assume that consumers and merchants that adopt and accept cards also do so for CBDC and, therefore, assume that cards and CBDC have the same adoption and acceptance rates (Figure 2).[18] A CBDC designed as a card (panel (a)) would lead to a usage share of only 0.263 for CBDC (reduced from 0.280) and usage shares for cash and cards of 0.474 (from 0.439) and 0.263 (from 0.280), respectively. A CBDC designed as cash (panel (b)) would lead to a usage share of only 0.285 for CBDC (from 0.371) and usage shares for cash and cards of 0.451 (from 0.371) and 0.264 (from 0.257), respectively. For a hybrid, card-like CBDC ($\lambda = 0.8$) the usage share of CBDC is 0.266 (from 0.295) and usage shares of cash and cards are 0.470 (from 0.428) and 0.264 (from 0.276), respectively. For a hybrid, cash-like CBDC ($\lambda = 0.2$) the usage share of CBDC is 0.279 (from 0.350) and usage shares of cash and cards are 0.456 (from 0.387) and 0.264 (from 0.263), respectively. In sum, when we jointly constrain CBDC usage and assume that this joint constraint is identical to the card constraint, CBDC usage is lower while cash usage is higher, i.e. the stricter constraint on CBDC (and cards) relative to cash leads consumers to use cash. The rise in cash usage across all scenarios can be attributed to the introduction of more realistic adoption and acceptance constraints. Cash, with its universal adoption and higher acceptance rate compared to cards (and CBDC in this scenario), becomes the fallback option when consumers face any constraints in using other forms of payment.[19] With a joint constraint on adoption and acceptance CBDC usage is less free to vary, i.e. it depends less on CBDC design.[20] Assuming the CBDC constraints to be equal to the card constraints may be optimistic.[21] We finally investigate the sensitivity of CBDC usage to its adoption and acceptance rates jointly in the following subsection, too.

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[18]As said, the adoption, in the form of ownership, rate of cards is close to 100% and the acceptance rate of cards is not that far from that of cash (83.2% and 96.1%, respectively). Therefore, assuming one or the other does not make much difference. In the following subsection, we investigate the sensitivity of CBDC usage to its adoption and acceptance rates.

[19]The effect of acceptance appears to be stronger than the effect of adoption. This result, available upon request, is due to the fact that the acceptance rate of cards is lower than their adoption rate.

[20]Here, we are abstracting from the fact that CBDC design would affect CBDC adoption and acceptance, too. In the following we depart from this abstraction.

[21]As for acceptance, this assumption may be still realistic, especially as CBDC would be legal tender.

(a) Perceived card design   (b) Perceived cash design

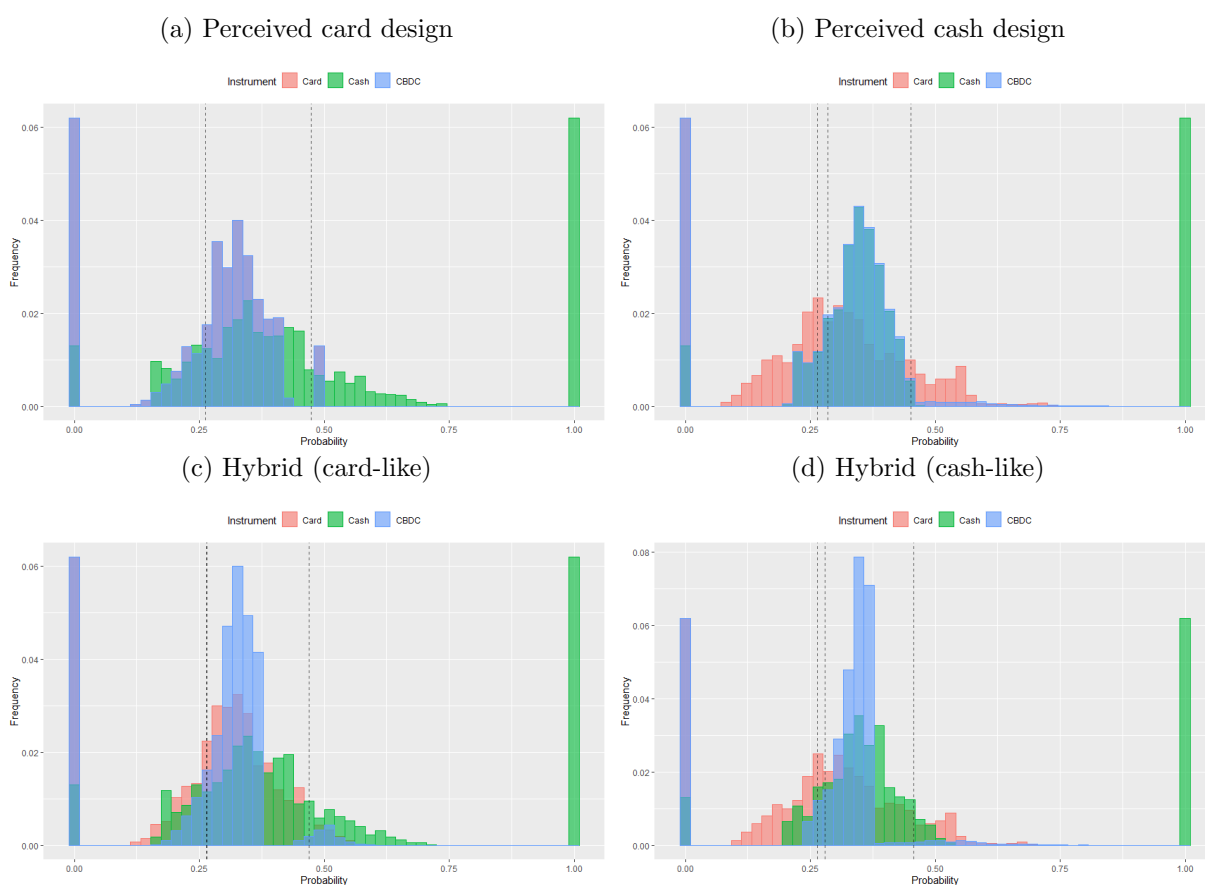(c) Hybrid (card-like)   (d) Hybrid (cash-like)

Figure 2: Conditioning on consumer adoption and merchant acceptance jointly: CBDC designs perceived to be as card and cash (upper panel) and hybrid (lower panel). Distributions of the usage choice probability for cash (green), cards (red) and CBDC (blue) at the consumer level. Vertical dashed lines represent the mean of these distributions. For each consumer the usage probabilities for cash, cards and CBDC add up to one. The tuning parameter λ is set to 0.8 for the hybrid, card-like design and to 0.2 for the hybrid, cash-like design.

5.2 Sensitivity analyses

5.2.1 Sensitivity to adoption and acceptance rates

In the previous subsections, we document the importance of CBDC adoption and acceptance for CBDC usage at the POS. We now perform a sensitivity analysis of the aggregate CBDC usage share by perturbing the adoption and acceptance rates. We discretize the adoption and acceptance rate into intervals and pick the start- or end-point of the interval as the rate. The rate interval vary from zero to one, i.e. we allow the CBDC rate to be lower than the card rate as well as higher. We divide these intervals in ten bits.

Figure 3 reports the scatter plot of aggregate CBDC usage shares and their 95% confidence

bands based on draws from the asymptotic distribution of the maximum likelihood estimates of the parameters.[22] In each panel, the estimated parameters are based on the model considering actual adoption and actual acceptance.

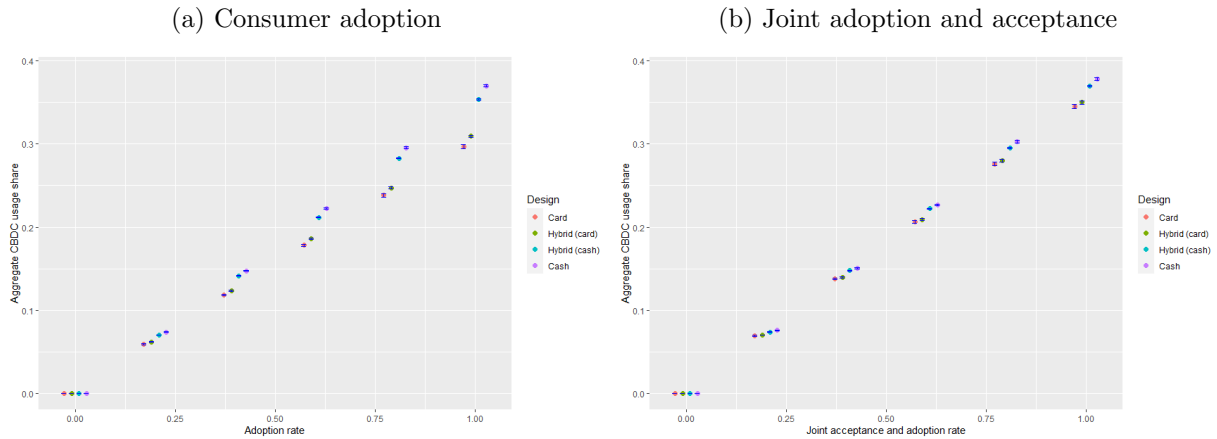| (a) Consumer adoption	(b) Joint adoption and acceptance

Figure 3: Aggregate CBDC usage share as a function of consumer adoption (panel (a)) and both adoption and acceptance (panel (b)). In each panel, we report four different CBDC designs: card, cash, hybrid (card) and hybrid (cash). Confidence intervals (95%) rest on the asymptotic normality of maximum likelihood estimates. The estimated parameters are based on the model considering actual adoption (panel (a)) and actual adoption and acceptance (panel (b)). Hence, the aggregate shares of panel (b) should be compared with their respective chart, Figure 2. When the simulated adoption and acceptance rates are higher than the actual ones, the aggregate shares are also higher.

Panel (a) reports the aggregate CBDC usage share as a function of the adoption rate. Obviously, an adoption rate of 0% leads to an aggregate CBDC usage share of 0. As the adoption rate increases, the aggregate CBDC usage share increases, too. Interestingly, this increase is roughly linear. When the adoption rate hits one we note maximum variation among designs, falling in the range 0.297 (card design) - 0.370 (cash design). Panel (b) displays the aggregate share against both the adoption and acceptance rates. Again, a 0% adoption and acceptance imply a CBDC share of 0. As adoption and acceptance rise, the CBDC share rises. The differences in CBDC shares due to different designs is less pronounced after jointly conditioning on adoption and acceptance. When the joint rate hits one the CBDC share falls in the range 0.345 (card design) - 0.378 (cash design).

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[22]We run a simulation with 1000 draws. Moreover, the calculation of the 95% confidence bands around the aggregate share is based on multiple Bernoulli draws with success rate equal to the adoption and acceptance rates.

5.2.2 Sensitivity to each attribute design

In this subsection we analyze the effect of CBDC design on the CBDC usage share. We gauge the sensitivity of the aggregate CBDC usage share to the attribute design and the effect of the constant (unobserved attribute or card usage benefit) while keeping the CBDC default design (for the remaining attributes) to be that of a card or cash. To assess the impact of each attribute we vary λ between 0 and 1. Figure 4 show this attribute-by-attribute analysis with 95% confidence bands around the aggregate shares.

Figure 4 reports the variation in aggregate CBDC usage share when the default CBDC design is that of a card (red, left-hand axis) and that of cash (blue, right-hand axis). Without loss, the below description focuses on a default card design. Panel (b) reports the effect of perceived acceptance on the share of CBDC payments. When CBDC is perceived to be accepted as cash the aggregate share is highest around 0.288. This share tends to decrease when we move towards a perceived acceptance similar to a card and reaches ca. 0.280. Panel (c) shows the effect of transaction speed. The CBDC share is minimal when transaction speed is cash-like (ca. 0.261) and trends upward when speed reaches a card benchmark, up to ca. 0.280. Instead, when anonymity (panel (d)) is absent (as with a card) the CBDC share is miminal at 0.280 and drift upwards as anonymity increases until cash-like anonymity where it reaches ca. 0.292. When CBDC is as easy as cash (panel (e)), the CBDC share is minimal at ca. 0.260 and tends to increase to 0.280 when it gets as easy as a card. Similarly, when CBDC is perceived to be secure as cash (panel (f)) its share is minimal around 0.272. When CBDC has card-like safety features, the CBDC share raises to 0.280. Similar remarks hold for convenience defined as the benefit of not carrying cash (panel (g)), though the variation in the CBDC share here is higher and goes from ca. 0.234 to 0.280 (when CBDC gets as convenient as carrying a card). When CBDC has an instantaneous settlement scheme (as cash, panel (h)) the CBDC share reaches its highest at ca. 0.292, while the opposite is true if CBDC has settlement speed as that of card (ca. 0.280). Similarly, a cash-like CBDC is perceived to be more useful for budgeting (as its share reaches ca. 0.299), while a card-like one delivers a share of ca. 0.280 (panel (i)). For all attributes, remarks are similar in case of a cash-equivalent CBDC, although the level share is higher.

Finally, panel (a) assesses the effect of the unobserved attributes as represented by the

constant (card usage benefit). When the constant is cash-like the CBDC shares reaches its highest value of ca. 0.436, while when it is card-like the CBDC share drops dramatically to ca. 0.280, as card usage is estimated to be costly. Again, the same holds in case of a cash-equivalent CBDC, although the level share is lower. Twisting the constant towards cash while keeping the attributes as card-like leads to a CBDC share exceeding the share under a cash design, as card usage benefit is estimated to be negative, i.e. a cost. Hence, by tuning the constant to be cash-like CBDC demand increases and, joint with card-like features, demand can be pushed up above the cash benchmark. However, as the constant contains the unexplained leftover, this remark is of little use for practical CBDC design, as it indicates that CBDC usage is still mostly driven by the unobserved attributes rather than the observed ones. Nevertheless, the key takeaway is that CBDC usage share is maximal when CBDC is card-like for transaction speed, ease of use, safety and convenience, while it is maximal when CBDC is cash-like for (perceived) acceptance, anonymity, settlement speed and usefulness for budgeting.[23] What is driving the variation induced by the unobserved attributes? Can modeling adoption reduce this variation?

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[23]Being the share a monotonic function of the attributes, it is easy to determine the optimal design, i.e. the optimal λ. We report quantitative estimates of the best and worst design scenario after modelling adoption in the following section.
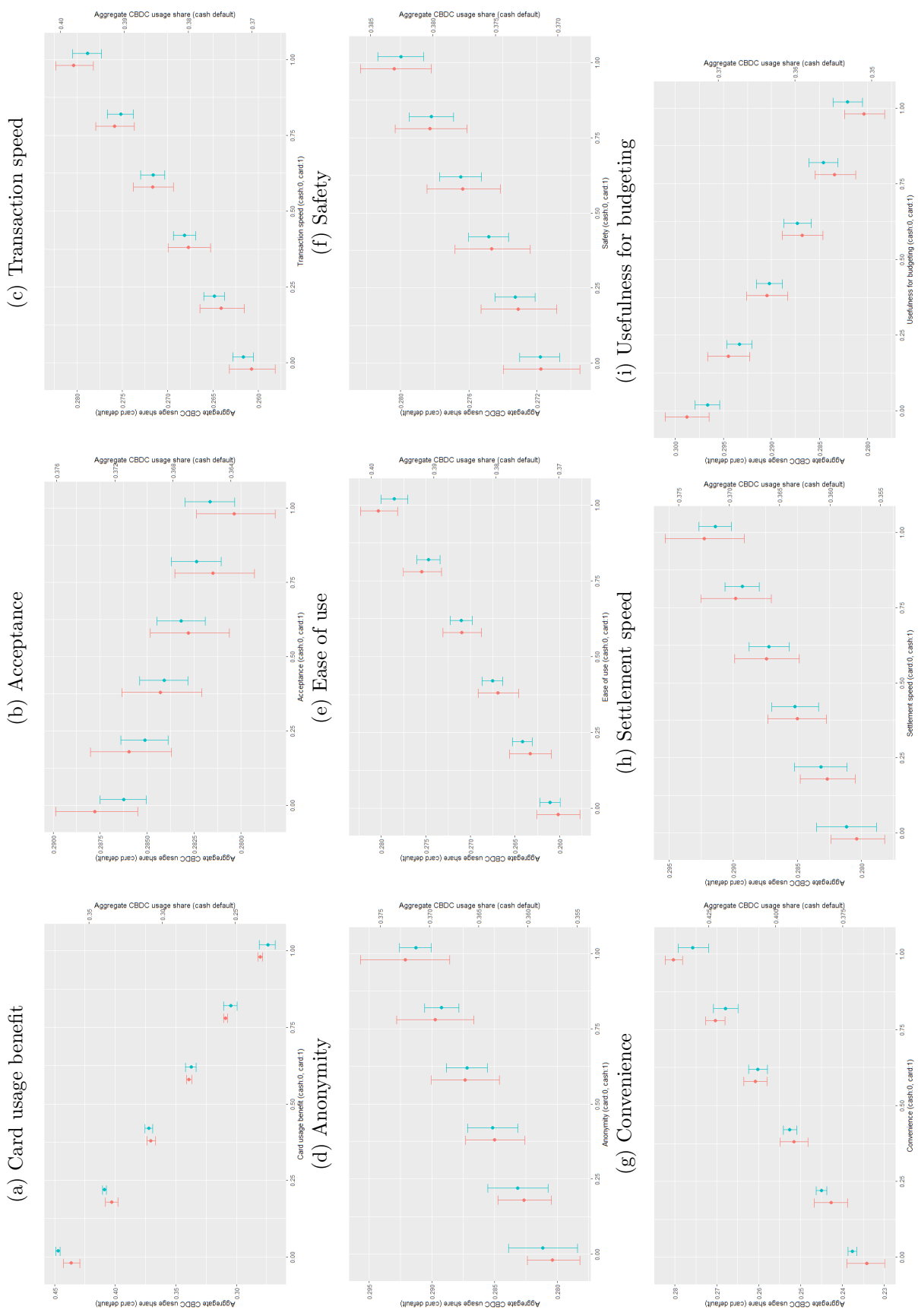
Figure 4: Aggregate CBDC usage share as a function of each attribute and the unobserved attributes (card usage benefit). The default CBDC design as a card is reported in red (left-hand axis), while the default CBDC design as cash is reported in blue (right-hand axis).

6 Model for adoption decision

In our initial usage model, we assume universal adoption of all means of payments. Subsequently, we relax this assumption by exogenously conditioning on consumer adoption (in the form of ownership of a means of payment). Also, we perform a sensitivity analysis to the adoption rate and show that CBDC usage is heavily affected by adoption, i.e. it varies greatly depending on whether CBDC is adopted or not. However, the 'ownership' approach does not consider potential, realistic adoption costs. To accurately analyze the transactional demand for CBDCs, it is critical to model adoption in a more realistic manner.

6.1 Importance of realistically modelling adoption

Diffusion of new technologies typically follows a gradual pattern, with early adopters facilitating the transition for subsequent users, and this is also true in the case of retail payments technologies (Stokey (2021)). The lag between invention and widespread adoption of these technologies can vary considerably, with disparities often attributable to a multitude of factors, including the presence of predecessor technologies (Comin & Hobijn (2004), Comin & Hobijn (2010)). This gradual diffusion is not exclusive to broader technologies, but is equally the case for retail payment technologies (Alvarez et al. (2023)). Although CBDC designs leverage on already existing technologies, CBDCs might still face significant adoption barriers as a newly introduced means of payment (Zamora-Pérez et al. (2022)), especially considering the existence of cash and well-functioning private digital alternatives to CBDC.

Previous attempts to model payment method adoption, e.g. Huynh et al. (2020), relies on card ownership as a proxy for adoption propensity. However, we argue that this approach may not be applicable to emergent means of payments, e.g. mobile payments and CBDCs, which are associated with higher adoption costs. Therefore, we consider card ownership an unrealistic proxy for adoption propensity in the context of these newly introduced means of payments, e.g. CBDC, and we rather argue that a proper proxy should capture potential adoption frictions.

As an alternative, we use self-reported preferences for mobile payments as a proxy for adoption propensity of new technologies. This choice is motivated by two considerations. First, cards represent a mature technology, with widespread acceptance and usage. The adoption dynamics

for such a well-established technology is fundamentally different from those of newly introduced payment methods, and hence the latter need a different approach to modelling their adoption.[24] Second, a (reported) 'preference' proxy offers a more conservative proxy compared to 'availability' proxies (e.g. card ownership). The 'preference' approach could raise the question: is mobile app downloads (i.e. an 'availability' proxy) a more suitable proxy for adoption? No, downloading a mobile payment app is a low-effort action that does not necessarily indicate a preference over other payment methods, nor does it ensure usage. Preferences for mobile payments provide a stricter and more reliable proxy for adoption than app downloads alone. In sum, how preferences can effectively serve as a proxy for adoption? Preferences represent a crucial, initial step for changing payment behavior. Aligning payment behavior with evolving preferences takes time and involves overcoming potential barriers (Van der Cruijsen *et al.* (2017)). There is a well-documented gap between consumer preference for its means of payment and its actual usage, and this is also the case of the euro area (ECB (2020), ECB (2022a)). Therefore, the 'preference' approach provides a more nuanced and realistic approach to model the adoption of emerging payment methods, e.g. CBDCs.

6.2 Adoption model

Given the above remarks, we augment our adoption model and make it multinomial by adding mobile applications. Another important novelty of our approach is that we model the adoption decision as a 'bundle expansion' decision. Essentially, a consumer might initially only have cash, but can progressively expand her 'bundle' of payment methods to include cards and newer payment technologies (e.g., mobile applications), provided these additions to her wallet offer enough utility. This framework allows to take into account the potential benefits and costs associated with each expansion of the bundle. We report below the model essentials and relegate

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[24]The high potential adoption cost of a CBDC could be understood in light of the history of mobile payments. Mobile payment services were first introduced in Europe in the early 2000s and saw a surge of interest despite the burst of the internet hype (Dahlberg *et al.* (2008)). However, many of these early services failed, and most of the dozens of services available in EU countries in the early 2000s have been discontinued. Today, the mobile payments market is growing and is highly competitive, with many options available to consumers. Our use of mobile payment preferences as a proxy for CBDC adoption can be considered optimistic, given that mobile payments have been around for two decades and have undergone significant maturation, despite still representing a small share of payment transactions. A CBDC would leverage the existing technology and consumer preferences of mobile payments, but its adoption could still face significant challenges.

a model summary to the Appendix A.

Consumer i faces now an adoption decision prior to the usage decision. The adoption decision of a bundle of payment instruments $b \in \mathcal{B}$ from $\mathcal{J}$ depends crucially on a cost-benefit analysis of adopting b. For example, cards and applications may face adoption costs. Although cashless instruments give an option to pay whenever a merchant does not accept cash (optionality) and/or let the consumer avoid having to carry cash or withdrawing physically at an ATM, they may be associated with maintenance costs (e.g. fees for cards) or switching costs (e.g. learning a new technology for applications). We argue that the CBDC adoption decision can be more realistically modelled by benchmarking it to mobile applications and, therefore, we consider the preference for mobile applications rather than card ownership as a proxy for the propensity to adopt a new means of payment. We assume that (i) the adoption cost parameter c_b is embedded in the adoption cost function $a_{i,b} = c_b - \epsilon^a_{i,b}$, where $b \in \mathcal{B}$ is a bundle of means of payment out of the superset of bundles; (ii) $c_b = \sum_j c_{j,b}$, where $j \in b$ and $c_{\{cash\}} = c_{cash,\{cash\}} = 0$; and that (iii) the error, or adoption shock, $\epsilon^a_{i,b} \overset{i.i.d.}{\sim} Gumbel(0,1)$ is also standard Gumbel distributed, where "a" stands for the adoption stage.

Before using a means of payment, consumer i calculates the gross (over all transactions) expected maximum utility she would get from using a means of payment belonging to the adopted bundle. The consumer faces risk over the utility as she does not observe the utility shock, but knows only its distribution.[25] The gross utility is netted by the cost of adoption, yielding

$$u^a_{net,i,b} = u^a_{i,b} - c_b + \epsilon^a_{i,b} \tag{8}$$

where $u^a_{i,b} = \sum_{l=1}^{L} \mathbb{E}_\epsilon(\max_{j \in b} \tilde{u}_{i,l,j})$ and, in turn, $\tilde{u}_{i,l,j} = \tilde{v}_{i,l,j} + \epsilon_{i,l,j}$ is the noisy usage utility at the time of adoption and $\tilde{v}_{i,l,j} = \alpha' \mathbf{x}_{i,j} + \gamma'_j \mathbf{z}_{i,l}$ is the utility function based on the observed attributes. Under the assumption that cash is universally adopted and in case of $\mathcal{B} = \{\{cash\}, \{cash, card\}, \{cash, card, app\}\}$, the adoption choice probability can be obtained as

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[25] Moreover, the consumer can calculate her utility based only on the attributes known to her, and the unobserved attributes, as represented by the constant, are considered by her as noise, too.

$$\mathbb{P}_{i,b} = \frac{e^{u^a_{i,b} - c_b}}{e^{u^a_{i,\{cash\}}} + e^{u^a_{i,\{cash,card\}} - c_{\{cash,card\}}} + e^{u^a_{i,\{cash,card,app\}} - c_{\{cash,card,app\}}}} \tag{9}$$

where $c_{\{cash,card,app\}} = c_{card,\{cash,card,app\}} + c_{app,\{cash,card,app\}}$. Contrarily to the usage decision in which instruments are substitutes, the adoption decision involves a 'bundle expansion'.

Estimation relies on observing consumers' preferences for multiple means of payments (survey question QQ3 and QQ3A, Appendix C). These preferences serve as a proxy for the adoption propensity of a specific bundle b. As the usage parameters affect the expected utility in the adoption stage and usage is conditional on adoption, we have to estimate the parameters jointly. We estimate the model parameters by numerical maximum likelihood (see Appendix A). The log-odds ratios are given by

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card\}}}{\mathbb{P}_{i,\{cash\}}}\right) = (u^a_{i,\{cash,card\}} - u^a_{i,\{cash\}}) - c_{\{cash,card\}} \tag{10}$$

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card,app\}}}{\mathbb{P}_{i,\{cash\}}}\right) = (u^a_{i,\{cash,card,app\}} - u^a_{i,\{cash\}}) - c_{\{cash,card\}} - c_{\{cash,card,app\}} \tag{11}$$

and

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card,app\}}}{\mathbb{P}_{i,\{cash,card\}}}\right) = (u^a_{i,\{cash,card,app\}} - u^a_{i,\{cash,card\}}) - c_{\{cash,card,app\}} \tag{12}$$

The estimated parameter for the adoption cost represents the effect of this cost on the log-odds ratio for adoption, while the usage parameters enters nonlinearly the calculation of the expected utility of adoption, $u^a_{i,b}$.

6.3   Results

6.3.1   Estimates

Table 3 reports the results. Column (1) shows the mobile-applications adoption-stage estimates when usage is conditional on adoption, while column (2) shows the same estimates when usage is conditional on both adoption and acceptance. Adopting a mobile application is costly for

consumers: the adoption cost parameter for mobile applications is positive and large in magnitude (3.499 and 3.484, respectively).[26] The estimated coefficients for the payment instrument attributes are robust: they are highly statistically significant with unchanged sign. Moreover, their magnitude increases substantially. On the contrary, the effect of the unobserved attributes embedded in the constant (card usage benefit) is greatly reduced (-0.137 and 0.052, respectively) and is absorbed by the payment instrument attributes and the mobile-applications adoption cost. As mentioned previously, the parameters for the attributes have a linear interpretation in the usage stage, while they have a nonlinear interpretation in the adoption stage. The coefficients have to be transformed by plugging them in $u^a_{i,\{cash,card\}}$ and $u^a_{i,\{cash,card,app\}}$.

6.3.2 CBDC simulation

Next, we introduce a CBDC and evaluate the adoption propensity of consumers for a wallet containing cash, cards and CBDC, where CBDC shares the same adoption cost as of applications and is designed to have card-like attributes ($\lambda = \mathbf{1}$). Figure 5, panel (a), reports the distribution of the adoption choice probabilities at the consumer level. This distribution is positively skewed: it has a long right tail and most statistical mass is concentrated in the first decile. For an app-like CBDC, the aggregate CBDC adoption share is around 0.075. Only few consumers are willing to adopt a CBDC with an app-like adoption cost. Conditional on these adoption probabilities and rate, we can calculate the usage probabilities. To do so, we generate an adoption vector taking value one whenever a consumer has an adoption probability greater than a certain quantile, function of the rate. As before, this adoption vector constrains the usage probability at the POS. Figure 5, panel (b), shows the distribution of usage probabilities at the consumer level. This distribution is even more heavily skewed: most of the statistical mass is concentrated on a zero-probability level. The residual mass is spread over the unit interval. For an app-like CBDC, the aggregate CBDC usage share is only 0.026. Not all the consumers who adopt CBDC (a few), use it at the POS.[27]

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[26]Moreover, adopting a mobile application is much more costly than adopting a card. Contrary to Huynh *et al.* (2020), cards bear an adoption cost, too. This result is available upon request.

[27]We run the simulation and plot the same distributions by varying the design, i.e. λ. The key takeaway is that as the design becomes more cash-like, the CBDC adoption and usage probabilities increase, but this increase is marginal. Results are available upon request.
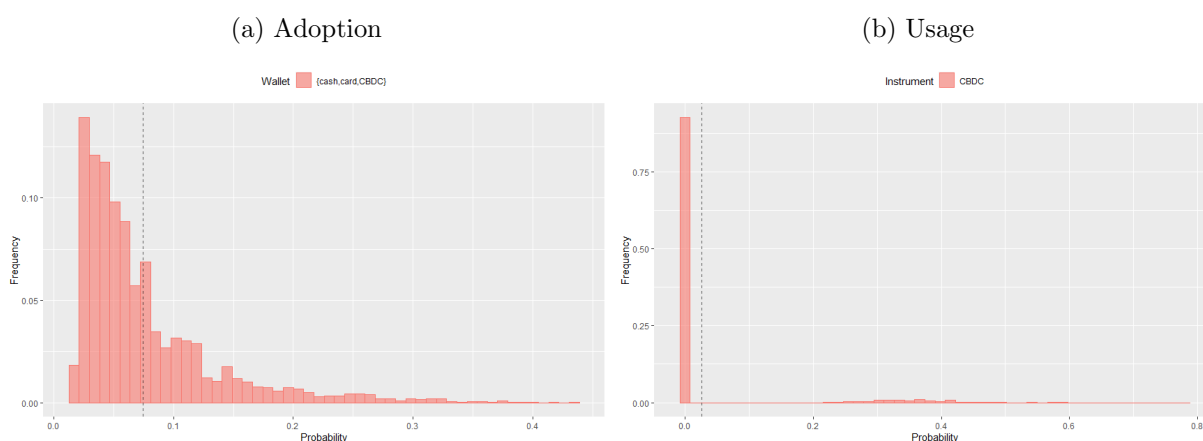
Figure 5: Distributions of the adoption and usage choice probabilities for the wallet including cash, cards and CBDC and for the payment instrument CBDC (panel (a) and (b), respectively).

6.3.3 Drivers of the adoption cost

The adoption cost of mobile payment applications is high under our 'bundle-expansion' framework. This finding suggests that newly introduced means of payments, such as a CBDC, may face a similar, if not a greater barrier. What are the drivers of this cost and how can a central bank reduce it? Assessing the extent to which a central bank can leverage these drivers to increase CBDC adoption requires the identification of an exogenous shock that changes consumer payment behaviour.

The COVID-19 pandemic serves as an ideal natural experiment, as it exogenously limited the options of using cash and PIN-based card payments in the euro area as documented by Tamele *et al.* (2021). The pandemic shock introduced euro-area consumers to alternative means of payment and, more generally, to finance apps (Fu & Mishra (2022)). Exploiting the pandemic shock aligns with the framework proposed by Crouzet *et al.* (2023), who find that an exogenous contraction of cash availability led to the adoption of mobile wallets. The SPACE 2022 survey contains two questions related to the change in behaviour linked to the pandemic shock: 1) first, consumers are asked whether they use cash more or less frequently in physical locations since the pandemic started; 2) then, consumers who use cash less often are asked the reasons that led them to use less cash.[28] The information on changed payment habits can be used to conduct a counterfactual analysis: consumers who switched behaviour (i.e. who employed less

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[28]See question QQ19C following QQ19A in Appendix C6.

cash, indicating more flexible habits) would be more prone to drive the CBDC uptake. The persistence of habits (defined by Kalckreuth *et al.* (2014) as the long-lasting experience with a payment instrument) are known to be an important determinant of payment preferences. Here we define habit flexibility as the willingness to incrementally use new means of payments (or, in the 'bundle-expansion' framework, to incorporate new means of payment to the consumers' wallet). The second question on the reasons of switching behaviour can be used to infer the drivers of adoption of a new means of payment, such as CBDC, that the central bank can leverage to augment transactional demand for CBDC. A potential barrier to the adoption of mobile applications could be the difficulty consumers face in obtaining information about new payment methods. The role of information discovery in technology adoption is well-established in the literature (see seminal works of Griliches (1957) and Mansfield (1961)). During the pandemic, government and supply-side restrictions may have resulted in more opportunities for consumers to discover and learn about new payment methods. To test this hypothesis, we can exploit the data on consumers who changed payment behaviour because they discovered new payment instruments since the start of the pandemic.

Another candidate driver for the high cost associated with mobile applications could be the nascent state of a country in terms of its mobile payment infrastructure. Wide availability of applications, possibly interoperable, would make it easier for individuals to adopt a new app-like CBDC. On the other hand, in a country which still relies heavily on cash and has no retail payment infrastructure for mobile payments, consumers would find it harder to adopt an alien technology, associated with significant switching costs.[29] Recently, Brunnermeier *et al.* (2019) have argued that, in a digital setting, larger networks can provide more value to their users, enhancing the network effects of digital currencies. We extend this concept to our context where CBDC is introduced as a new payment instrument. We use the country-level diffusion of mobile applications for P2P and POS payments to understand how the payment environment affects adoption. We choose the country-level diffusion, i.e. the highest level of aggregation, to ensure exogeneity.[30] While individuals obviously contribute to the aggregate, this contribution

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[29]This conceptual framework draws from the work of Dowd & Greenaway (1993) on currency competition.

[30]Similarly, Dowd & Greenaway (1993) use the logarithm of the number of users to proxy for diffusion, while we use the share of transactions made using each payment method. This measure reflects both the size and the intensity of use of each payment method's network, making it arguably more relevant in our context of retail

is marginal and we can take the aggregate diffusion as exogenous.

Methodologically, the cost of adoption, $c_b = \sum_j c_{j,b}$, in the consumers' utility $u_{net,i,b}^a = u_{i,b}^a - c_b + \epsilon_{i,b}^a$ can be decomposed as

$$c_b = \tilde{c}_b + \tilde{\mathbf{c}}_{d,b}'\mathbf{d}_i = \tilde{c}_b + \tilde{c}_{info,b}info_i + \tilde{c}_{diff,b}diff_{co} \tag{13}$$

where $b = \{cash, card, app\}$, $\mathbf{d}_i$ is a vector of drivers, $\tilde{\mathbf{c}}_{d,b}$ are driver-specific variations in the adoption cost and $\tilde{c}_b$ is the leftover cost. We include two drivers in $\mathbf{d}_i$ which are related to adoption and are targetable by the central bank. The vector $\mathbf{d}_i$ includes information discovery[31], $info_i$, and mobile-applications diffusion, $diff_{co}$, where co stands for country. For estimation, the usual normalization applies, i.e. $\tilde{c}_{\{cash\}} = 0$ and $\tilde{\mathbf{c}}_{d,\{cash\}} = \mathbf{0}$.

When introducing a CBDC, the counterfactual estimates rely on two key facts. First, that the central bank is able to reach consumers with flexible habits via a targeted information campaign, thereby inducing those consumers to increase their propensity to adopt CBDC. Differently put, the utility associated to a bundle including CBDC would receive a boost for those consumers subject to the campaign. On the contrary, the utilities associated to existing bundles do not gain from these actions and, therefore, the latter become less attractive. Second, that a randomly drawn country is able to reach a mobile-apps diffusion beyond what currently observed. For consumers living in that country, this diffusion exogenously boosts the utility from adopting CBDC and, accordingly, the propensity to adopt it, thus increasing the aggregate CBDC market share.

Table 4 reports the estimates. Information discovery reduces significantly the adoption cost of mobile applications. For consumers with more flexible habits, discovering a means of payment may have had a long-lasting impact on adoption since the start of the pandemic. Mobile-apps diffusion reduces the adoption cost of mobile applications, too. The higher the diffusion, the lower the adoption cost, the higher the CBDC adoption probability. We conduct a counterfactual analysis in the next section.

payments. By expressing the usage of each method as a share of total transactions, we can directly compare the adoption of new methods with traditional ones such as cash and cards, thus better assessing the competitive dynamics in the 17 countries' markets analysed.

[31]See answer 7 of question QQ19C in Appendix C6.

6.4 Sensitivity analyses

6.4.1 Sensitivity to each attribute design

In this subsection we report the effects of the observed attributes on adoption. The direction of the effects on adoption is identical to the direction of the effects on usage (Figure 6). Nevertheless, the effects on adoption can be nonlinear and, moreover, can go in opposite direction depending on whether the default design is cash-like or app-like (e.g. acceptance). For some attributes, e.g. anonymity, the effects on adoption are stronger than the effects on usage. By modelling adoption, we show that design options play an important role for the CBDC uptake, especially when all attributes are jointly designed optimally.

As previously mentioned, we now assess the best and worst design scenario and their implications for the CBDC uptake. Table 5 reports the λ leading to these designs. In the best-design scenario, CBDC is card-like for transaction speed, ease of use, safety and convenience, while it is cash-like for (perceived) acceptance, anonymity, settlement speed and usefulness for budgeting. The opposite holds true in the worst-design scenario. Based on these designs, we can compute the maximum and minimum CBDC usage and adoption shares. Figure 7 reports these two scenarios with their 95% confidence bands. CBDC adoption and usage are maximal under the best design, while they are minimal under the worst design. Under the best design, the aggregate CBDC adoption share is about 0.122, while is about twice as small under the worst design (i.e. about 0.065). Similarly, the aggregate CBDC usage share can be increased up to about 0.061 if CBDC is optimally designed, while under the worst design this shares falls at about 0.025 (three times smaller).
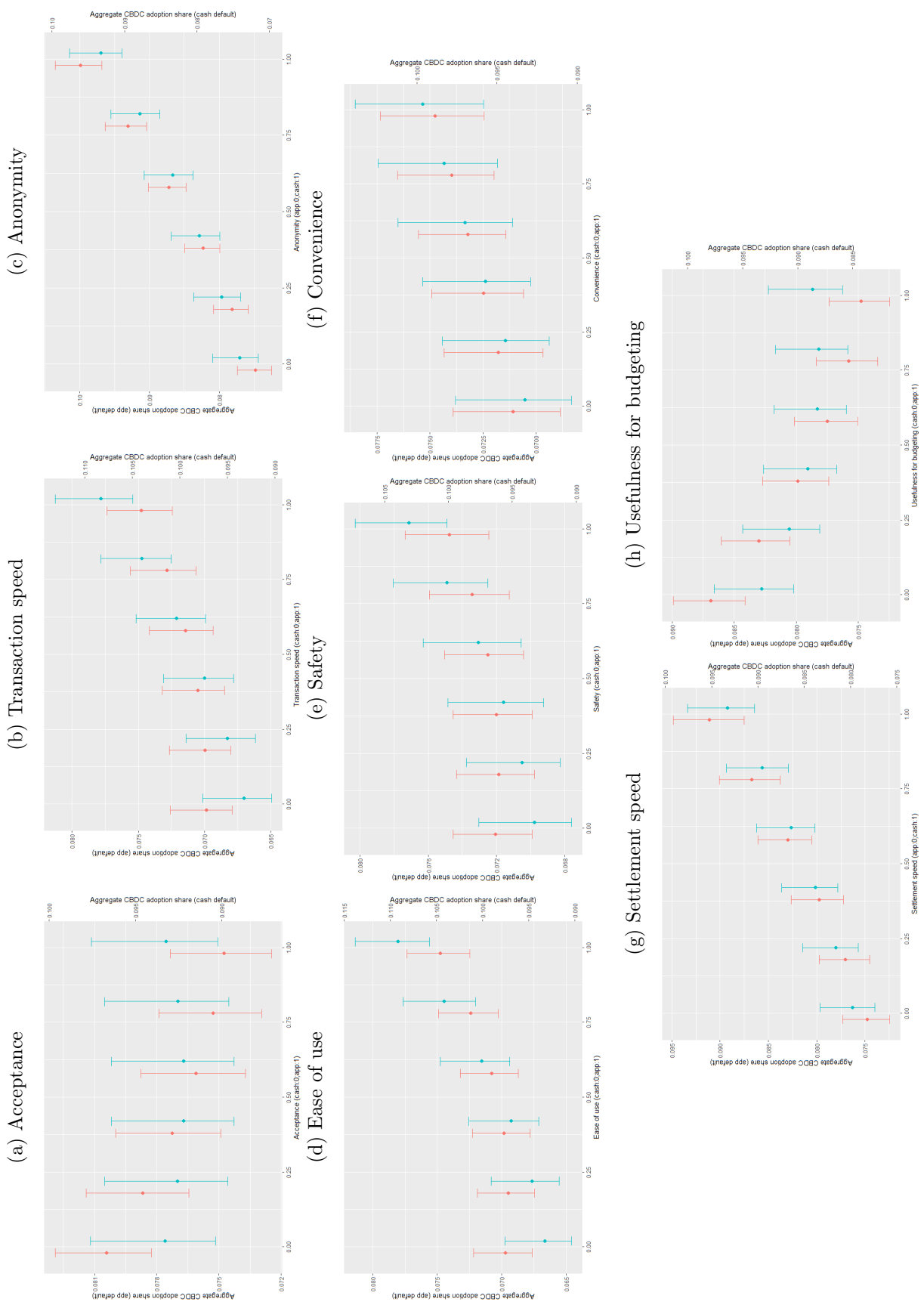
Figure 6: Aggregate CBDC adoption share as a function of each attribute. The default app-like design is reported in red (left-hand axis), while the default cash-like design is reported in blue (right-hand axis).
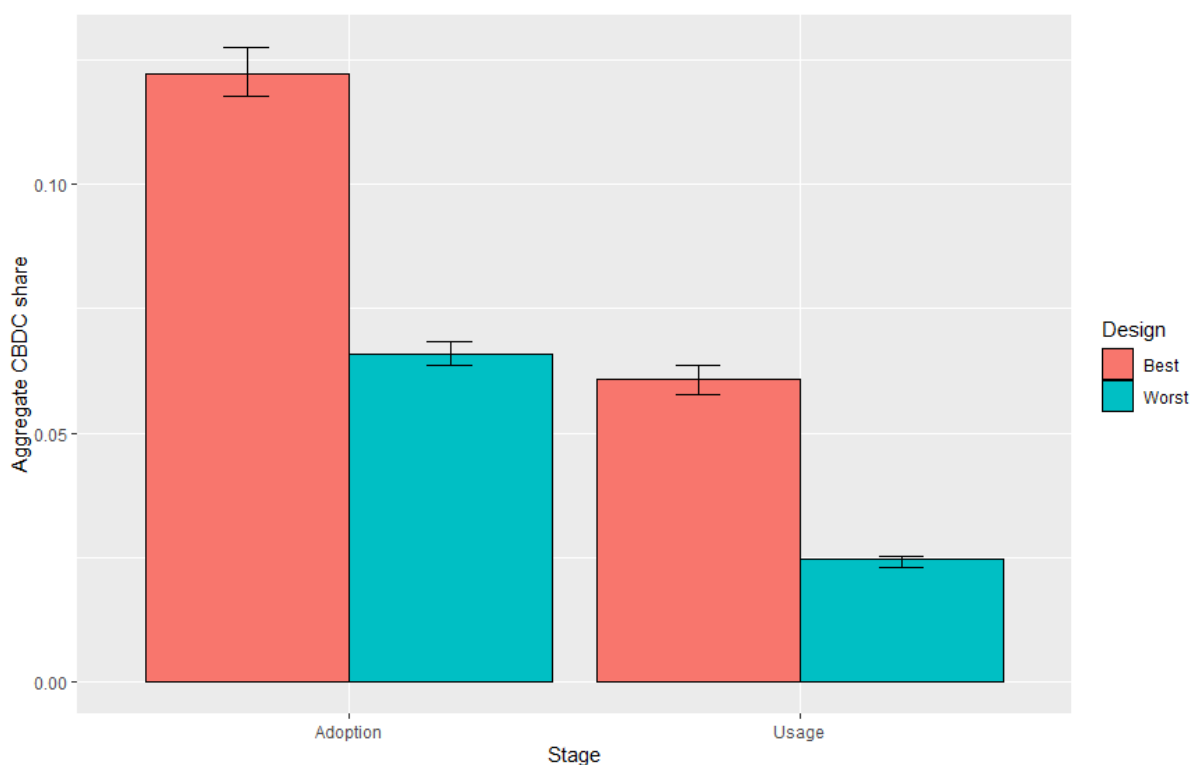
Figure 7: Aggregate CBDC adoption and usage shares (y-axis) based on the best (red bars) and worst (blue bars) design scenario. The x-axis reports the stage: adoption and usage. Confidence intervals (95%) rest on the asymptotic normality of maximum likelihood estimates. The best design involves an app-like CBDC for transaction speed, ease of use, safety and convenience, while a cash-like CBDC for (perceived) acceptance, anonymity, settlement speed and usefulness for budgeting. The worst design involves the reverse.

6.4.2 Sensitivity to the adoption cost

In this subsection we evaluate the sensitivity of the CBDC adoption and usage share to the adoption cost.

Figure 8, panel (a), reports the sensitivity of the aggregate CBDC adoption share to the adoption cost, which varies between being null to being equal to the adoption cost of mobile applications. The default CBDC design is that of a mobile application along the left-hand axis (red) and that of cash along the right-hand axis (blue). The following description focuses on the application design. The CBDC adoption share is highly sensitive to the adoption cost. The adoption share of CBDC is just 0.074 when its adoption is that of mobile applications, while it increases up to 0.663 if the adoption cost is zero. Similar remarks hold true in the case of a

cash-like design.

The above analysis discusses the adoption probability. Even if consumers decide to adopt an application-like CBDC, consumers may decide not to use it at the POS, i.e. the adoption probability provides an upper bound for usage at the POS. In what follows we analyse the aggregate CBDC usage share as a function of the adoption cost. We use the adoption probability to generate an adoption vector to constrain usage at the POS. Figure 8, panel (b), reports the sensitivity of the aggregate CBDC usage share to the adoption cost, which varies between being null to being equal to the adoption cost of mobile applications. Again, the default CBDC design is that of a mobile application along the left-hand axis (red) and that of cash along the right-hand axis (blue). The following description focuses on the application design. The CBDC usage share is also highly, though less sensitive to the adoption cost. The usage share is 0.027 when the CBDC adoption cost approaches that of an application, while it is 0.209 if the CBDC adoption cost is null. Similar remarks hold true in the case of a cash-like design. Hence, CBDC usage at the POS is lower than its adoption.

<div align="center">(a) Adoption   (b) Usage</div>
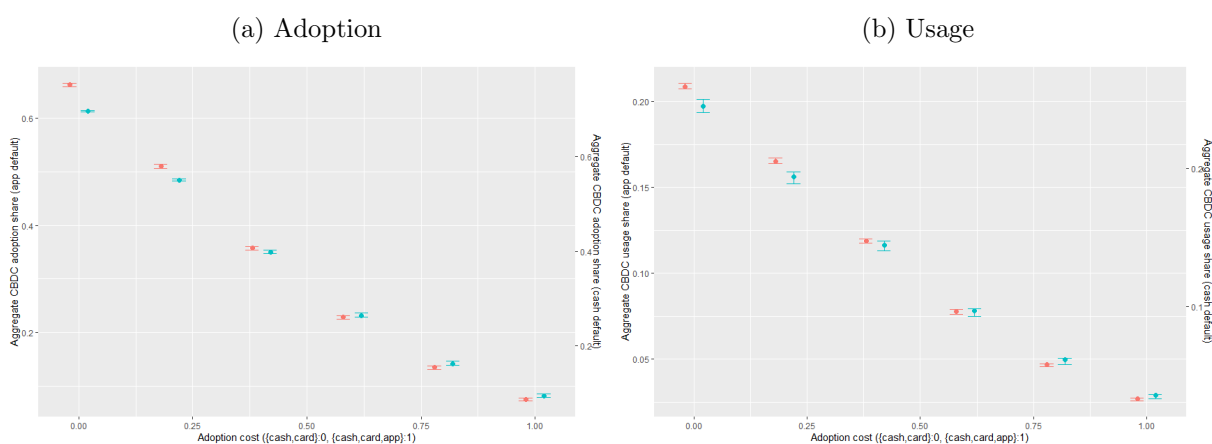

Figure 8: Aggregate CBDC adoption and usage shares as a function of the adoption cost (panel (a) and (b), respectively).

6.4.3 Sensitivity to the cost drivers

The counterfactual exercises involve

$$\hat{c}_b = \hat{\tilde{c}}_b + \hat{\tilde{c}}_{info,b}swit_i + \hat{\tilde{c}}_{diff,b}di\tilde{f}f_{co} \tag{14}$$

where $\hat{\tilde{c}}_{info,b}$ is the estimated coefficient attached to information discovery, $swit_i$ is the control identifying consumers who switched behaviour during the pandemic, $\hat{\tilde{c}}_{diff,b}$ is the estimated coefficient attached to mobile-apps diffusion and $\tilde{diff}_{co}$ is a counterfactual diffusion.

The first counterfactual assesses what would be the CBDC uptake if the central bank was able to target the subsample of consumers with flexible habits with an information campaign.[32] Figure 9 shows how the CBDC adoption and usage shares react to this campaign. Both shares increase: in particular, the adoption share increase by circa 2 p.p. (from 0.061 to 0.080), while an increase of about 0.4 p.p. (from 0.023 to 0.027) affects the usage share. This increase is thanks to the fact that $\hat{\tilde{c}}_{info,b}$ is negative and, therefore, it reduces the adoption cost of CBDC. This increase does not cover the whole variation induced by the adoption cost, but it is the portion we can attribute a causal interpretation given the data at hand.[33] Therefore, the central bank can induce higher CBDC adoption and usage beyond the design options.

The second counterfactual evaluates how diffusion of a new means affects the CBDC adoption and usage shares.[34] Figure 10 shows an s-shaped technology adoption and usage curve for CBDC as a function of mobile-applications diffusion. As mobile-applications diffusion increases, the probability of adoption and usage of CBDC increases non-linearly: slow for low app diffusion through early adopters; fast when diffusion is above 10%-15%; slow again when diffusion is above 50% and the technology is mature. In the hypothetical scenario of full saturation, the CBDC adoption share reaches almost 1, while the CBDC usage share does not go beyond 0.30, i.e. if every consumer in a country employed mobile apps, almost everybody in that country would be prone to adopt CBDC, while only a fraction would be willing to actually use CBDC.[35] Finally, the confidence bands around the usage curve reveal an heavily skewed distribution of the usage shares: there could be plausible usage curves lying below the depicted one.

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[32] To do so we switch off $\hat{\tilde{c}}_{diff,b}$ and focus only on $\hat{\tilde{c}}_{info,b}$.

[33] The central bank could also follow the complementary strategy to increase the adoption utility. One way to do it is to add a unique combination of features to CBDC, such as P2P and online functionalities. Unfortunately, we cannot test this complementary strategy with the data at hand, as P2P and online payment behaviour are clearly endogenous to the adoption proxy, i.e. the preferences for payment instruments.

[34] To do so we switch off $\hat{\tilde{c}}_{info,b}$ and focus only on $\hat{\tilde{c}}_{diff,b}$.

[35] Given their relative novelty, mobile payment apps still represent a small portion of POS and P2P payments in the euro area, averaging around 3.3% across our 17-country sample, with Finland having the highest share at 7.1%. Therefore, the adoption and usage curves above that threshold are based on extrapolation and should be interpreted with caution. This caution is further substantiated by the wide confidence bands associated with the projected CBDC adoption and usage shares exceeding this 7.1% threshold.
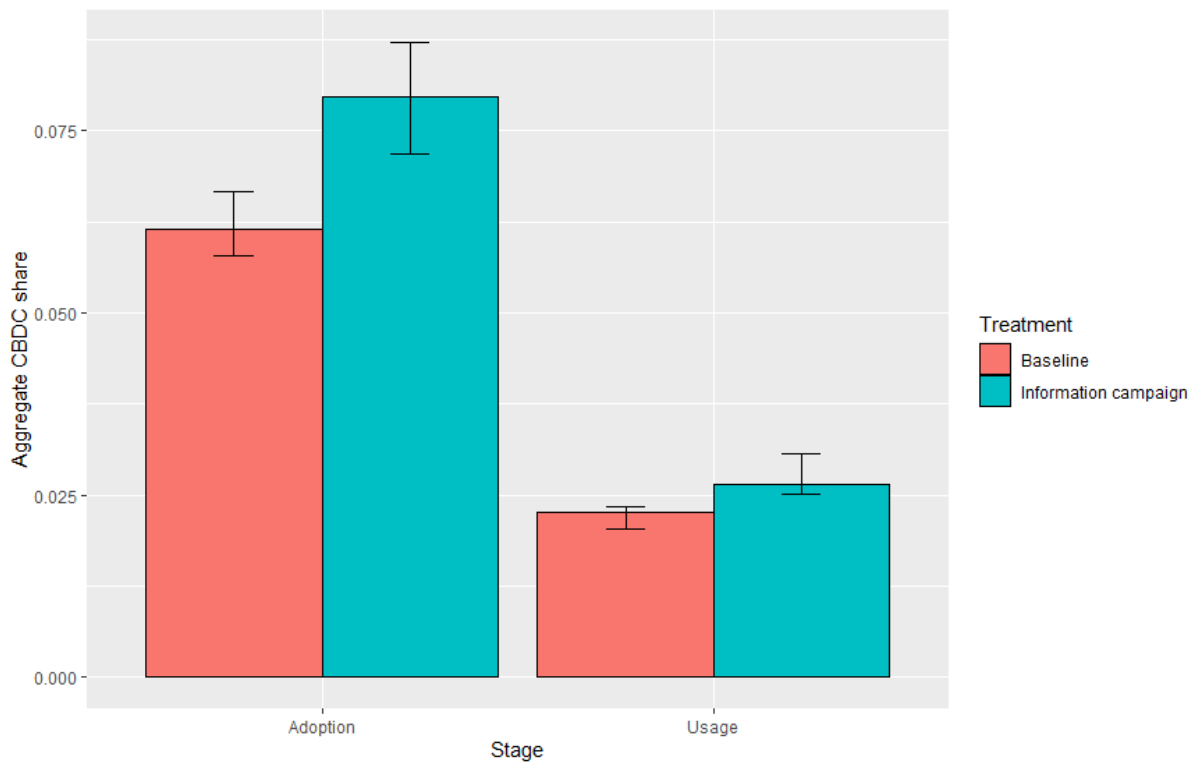
Figure 9: Aggregate CBDC adoption and usage shares (y-axis) under the baseline scenario (red bars) and after an information campaign (blue bars). The x-axis reports the stage: adoption and usage. Confidence intervals (95%) rest on the asymptotic normality of maximum likelihood estimates.

(a) Adoption   (b) Usage

Figure 10: Network effects: aggregate CBDC adoption (panel (a)) and usage (panel (b)) shares (y-axes) as a function of country-level mobile-applications diffusion for P2P and POS payements (x-axes, in %). Confidence intervals (95%) rest on the asymptotic normality of maximum likelihood estimates.

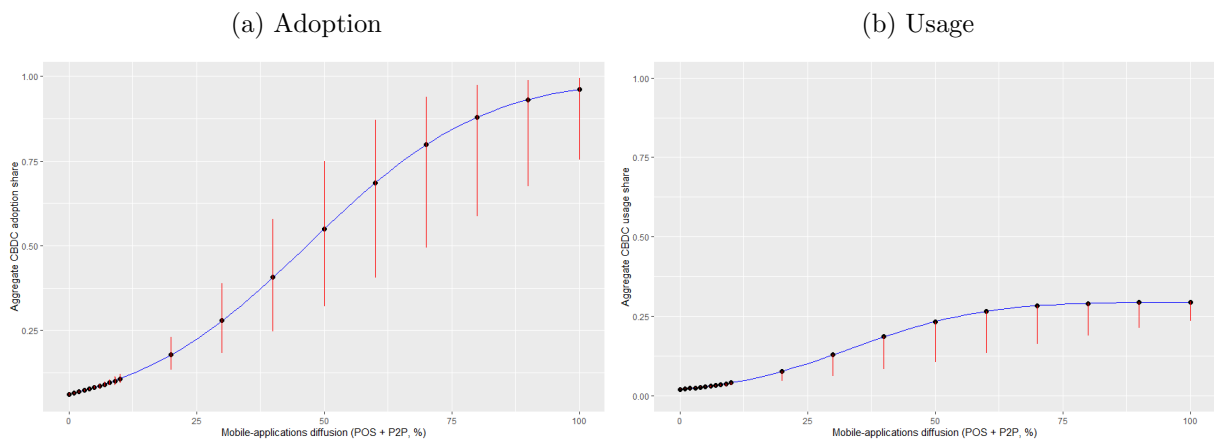# 7 Conclusion

Amid increasing interest in CBDCs and their role in retail payments, our paper addresses the relatively unexplored topic of CBDC transactional demand, with a particular emphasis on the potential adoption friction. This topic is important for informing CBDC policy decisions, but also for enriching the body of research on macroeconomic implications, which currently implicitly relies on CBDC demand scenarios.

We use cross-country survey data on payment behaviour and preferences to shed light on the demand for a CBDC as a means of payment. We develop a structural model of adoption and usage of means of payment and estimate CBDC usage and adoption based on individuals' preferences for existing payment method attributes. The novelty of our work with respect to the existing literature is fourfold: (1) we provide for the first time a quantitative framework to assess transactional demand for CBDC at the POS in a multiple-country setting by accommodating a wide range of CBDC design choices; (2) we model CBDC adoption as an addition to the 'bundle' of available payment means by explicitly disentangling the cost associated with the adoption of novel means of payment, such as mobile applications, which is crucial to understanding the potential barriers to CBDC adoption; (3) contrary to previous literature, we use data on mobile applications rather than card ownership to proxy the adoption propensity for CBDC. Cards represent a mature technology and their adoption dynamics is fundamentally different from those of new payment methods; and (4) we assess two potential drivers of the cost of adopting CBDC, information frictions and gradual diffusion of digital payment methods, and show how central banks may leverage them to facilitate CBDC adoption.

We show that the estimated demand for CBDC may be sensitive to the adoption cost of novel payment methods, identifying the primary reason why transactional demand might be lower than that estimated in the previous literature. We also show that CBDC demand could be increased if CBDC is designed optimally by fine-tuning (1) the payment method attributes (thus increasing utility) and (2) the drivers of the adoption cost (thus reducing cost). First, we show that CBDC design is optimal when it exhibits a combination of card-like features (for transaction speed, ease of use, safety and convenience of not carrying cash), coupled with cash-like features (perceived acceptance, anonymity, settlement speed and usefulness for budgeting). Most notably, if CBDC

is designed this way, the CBDC adoption share can be doubled and the CBDC usage share tripled. Second, we provide causal evidence that a targeted information campaign can reduce the CBDC adoption friction, hence increasing its adoption even though usage is not much affected. Also, we show that if the central bank is able to facilitate an environment conducive to the diffusion of mobile applications, the CBDC adoption friction can be further reduced, i.e. network effects can substantially boost CBDC adoption and, consequently, usage. Our study does not consider the role of distribution of payment service providers, the universality of use cases, and the possibility to save on fees. All these aspects are indeed important to potentially amplifying network effects, thus potentially boosting demand. For example, the obligation to distribute CBDC, making it universally available, could substantially accelerate network effects. Future research should be directed into incorporating these considerations.

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Appendix

Model summary

A1. Model for usage decision

Model

To recap, consumer i chooses instrument j with higher probability if $u_{i,l,j} > u_{i,l,k}$, where k is a means of payment other than j. Due to the unobserved utility preference shock, even if the usage utility of transacting with k instead of j is higher, instrument j may be chosen if its associated utility shock can sufficiently compensate. Denoting $f(\epsilon_i)$ the joint density of ϵ_i, the probability that consumer i chooses means of payment j is given by

$$\mathbb{P}_{i,l,j} = \int_{\epsilon} \mathbb{1}(v_{i,l,j} - v_{i,l,k} > \epsilon_{i,l,k} - \epsilon_{i,l,j}) f(\epsilon_i) d\epsilon_i, j \neq k$$

where k is a means of payment other than j and $\mathbb{1}$ is an indicator function. This probability shows that only differences in utility matters for consumer's choice and not the level utility. To obtain a particular functional form for the choice probability, we make the following assumption:

the utility shock $\epsilon_{i,l,j}$ follows a standard Gumbel or type I extreme value distribution, i.e. $\epsilon_{i,l,j} \overset{i.i.d.}{\sim} Gumbel(0,1)$. Accordingly, the choice probability of using means of payment j is given by

$$\mathbb{P}_{i,l,j} = \frac{e^{v_{i,l,j}}}{\sum_k e^{v_{i,l,k}}}$$

As the utility $v_{i,l,j}$ increases, the probability of choosing means of payment j increases, too. In the limit, if $v_{i,l,j} \to \infty$ then $\mathbb{P}_{i,l,j} \to 1$, while if $v_{i,l,j} \to -\infty$ then $\mathbb{P}_{i,l,j} \to 0$.

In the baseline model, we consider the simplest scenario of a binary model with two means of payment in the choice set $\mathcal{J}$, i.e. cash and cards (debit or credit), i.e. $j \in \{cash, card\}$. This simplification leads to

$$\mathbb{P}_{i,l,j} = \frac{e^{v_{i,l,j}}}{e^{v_{i,l,cash}} + e^{v_{i,l,card}}}$$

Estimation

Estimation relies on observing the payment choices of consumers. Let the payment choice $y_{i,l,j}$ be an observed categorical variable identifying whether consumer i chooses means of payment j in transaction l. The variable $y_{i,l,j}$ follows a generalized Bernoulli distribution, i.e. $y_{i,l,j} \sim Cat(\mathbb{P}_{i,l,j})$. Based on this distribution we can conduct maximum likelihood estimation. The likelihood function is given by

$$\mathcal{L}(\mathbb{P}_{i,l,j}; y_{i,l,j}) = \prod_{i=1}^{I} \prod_{l=1}^{L} \prod_{j \in \mathcal{J}} \mathbb{P}_{i,l,j}^{y_{i,l,j}}$$

Maximum likelihood estimation involves solving the following optimization problem

$$\underset{\alpha, \eta_j, \gamma_j}{\operatorname{argmax}} \; Log\mathcal{L}(\mathbb{P}_{i,l,j}; y_{i,l,j})$$

The first-order condition (also called score or gradient) of this optimization problem is non-linear in the parameters and, therefore, we cannot achieve an analytical solution. However, we can resort to a numerical one, e.g. via the Newton-Ralphson algorithm, as long as the likelihood function is globally concave. The estimated parameters represent effects on the log-odds ratio.

The log-odds ratio for any given means of payment j and k, $j \neq k$ is given by

$$ln\left(\frac{\mathbb{P}_{i,l,j}}{\mathbb{P}_{i,l,k}}\right) = v_{i,l,j} - v_{i,l,k} = \alpha'(\mathbf{x}_{i,j} - \mathbf{x}_{i,k}) + \eta_j - \eta_k + (\gamma_j - \gamma_k)'\mathbf{z}_{i,l}$$

The estimated parameters are the effects on the log-odds ratio thanks to the fact that the latter is linear in the parameters. Moreover, equation the log-odds ratio implies that choice of using j *versus* k does not depend on any other alternative other than j and k (i.e. it is independent from "irrelevant" alternatives).

In case of a binary model, i.e. with cash and cards as the only available means of payment, we have

$$ln\left(\frac{\mathbb{P}_{i,l,card}}{\mathbb{P}_{i,l,cash}}\right) = \alpha'(\mathbf{x}_{i,card} - \mathbf{x}_{i,cash}) + \eta_{card} - \eta_{cash} + (\gamma_{card} - \gamma_{cash})'\mathbf{z}_{i,l} \tag{15}$$

Normalizing the cash parameters, the numeraire, to 0, i.e. $\gamma_{cash} = \mathbf{0}$ and $\eta_{cash} = 0$, we have

$$ln\left(\frac{\mathbb{P}_{i,l,card}}{\mathbb{P}_{i,l,cash}}\right) = \alpha'(\mathbf{x}_{i,card} - \mathbf{x}_{i,cash}) + \eta_{card} + \gamma_{card}'\mathbf{z}_{i,l} \tag{16}$$

To obtain the estimated effects on the choice probabilities directly, i.e. to get the marginal or partial effects, we can reverse-engineer the log-odds ratio or calculate differences (as our attribute predictors are discrete, see next section) in choice probabilities.

A2. Model for adoption decision

Model

In sum, before using a means of payment, (rational) consumer i calculates the gross (over all transactions) expected maximum utility she would get from using a means of payment belonging to the adopted bundle. The consumer faces risk over the utility as she does not observe the utility shock, but knows only its distribution. Moreover, the consumer can calculate her utility based only on the attributes known to her, and the unobserved attributes, as represented by the constant, are considered by her as noise, too. This gross utility can be expressed as

$$u_{i,b}^a = \sum_{l=1}^{L} \mathbb{E}_\epsilon \left(\max_{j\in b} \tilde{u}_{i,l,j} \right)$$

where $\tilde{u}_{i,l,j} = \tilde{v}_{i,l,j} + \epsilon_{i,l,j}$ is the noisy usage utility at the time of adoption, and $\tilde{v}_{i,l,j} = \alpha'\mathbf{x}_{i,j} + \gamma'_j\mathbf{z}_{i,l}$ is the utility function based on the observed attributes. Equivalently,

$$u_{i,b}^a = \sum_{l=1}^{L} ln \sum_{j\in b} e^{\tilde{v}_{i,l,j}}$$

Consumers net this gross utility by the cost of adoption

$$u_{net,i,b}^a = u_{i,b}^a - a_{i,b} = u_{i,b}^a - c_b + \epsilon_{i,b}^a$$

yielding the adoption net utility. Therefore, as in the usage stage, the adoption choice probability can be obtained as

$$\mathbb{P}_{i,b} = \frac{e^{u_{i,b}^a - c_b}}{\sum_{b\in\mathcal{B}} e^{u_{i,b}^a - c_b}}$$

Under the assumption that cash is universally adopted, in case of $\mathcal{B} = \{\{cash\},\{cash,card\}\}$, we have

$$\mathbb{P}_{i,b} = \frac{e^{u_{i,b}^a - c_b}}{e^{u_{i,\{cash\}}^a - c_{\{cash\}}} + e^{u_{i,\{cash,card\}}^a - c_{\{cash,card\}}}}$$

where the cash parameter, the numeraire, is normalized so that $c_{\{cash\}} = 0$ and

$$\mathbb{P}_{i,b} = \frac{e^{u_{i,b}^a - c_b}}{e^{u_{i,\{cash\}}^a} + e^{u_{i,\{cash,card\}}^a - c_{\{cash,card\}}}}$$

where $c_{\{cash,card\}} = c_{card,\{cash,card\}}$. In case of a triple bundle (the multinomial case), i.e. $\mathcal{B} = \{\{cash\},\{cash,card\},\{cash,card,app\}\}$, we have

$$\mathbb{P}_{i,b} = \frac{e^{u_{i,b}^a - c_b}}{e^{u_{i,\{cash\}}^a - c_{\{cash\}}} + e^{u_{i,\{cash,card\}}^a - c_{\{cash,card\}}} + e^{u_{i,\{cash,card,app\}}^a - c_{\{cash,card,app\}}}}$$

where the cash parameter, the numeraire, is normalized so that $c_{\{cash\}} = 0$ and

$$\mathbb{P}_{i,b} = \frac{e^{u^a_{i,b}-c_b}}{e^{u^a_{i,\{cash\}}} + e^{u^a_{i,\{cash,card\}}-c_{\{cash,card\}}} + e^{u^a_{i,\{cash,card,app\}}-c_{\{cash,card,app\}}}}$$

where $c_{\{cash,card,app\}} = c_{card,\{cash,card,app\}} + c_{app,\{cash,card,app\}}$.

Estimation

Let the adoption propensity of a bundle $y^a_{i,b}$ be an observed categorical variable identifying if consumer i is willing to choose bundle b. Also here $y^a_{i,b} \sim Cat(\mathbb{P}_{i,b})$. The likelihood function can be obtained as

$$\mathcal{L}(\mathbb{P}_{i,b}; y^a_{i,b}) = \prod_{i=1}^{I} \prod_{b \in \mathcal{B}} \mathbb{P}_{i,b}^{y^a_{i,b}}$$

As the usage parameters affect the expected utility in the likelihood of the adoption stage and usage is conditional on adoption, we have to estimate the parameters jointly. Given the assumptions on the error terms, the joint likelihood is the product of the stage-specific likelihood functions of usage and adoption, where the usage likelihood is conditioned on adoption

$$\mathcal{L}(\mathbb{P}_{i,l,j|b}; y_{i,l,j}; \mathbb{P}_{i,b}; y^a_{i,b}) = \left(\prod_{i=1}^{I} \prod_{l=1}^{L} \prod_{j \in \mathcal{J}} \mathbb{P}_{i,l,j|b}^{y_{i,l,j}} \right) \left(\prod_{i=1}^{I} \prod_{b \in \mathcal{B}} \mathbb{P}_{i,b}^{y^a_{i,b}} \right)$$

where $\mathbb{P}_{i,l,j|b}$ is the usage probability conditioned on adoption and is defined above. The joint likelihood leads to the estimation problem

$$\underset{\alpha, \eta_j, \gamma_j, c_b}{\text{argmax}} \ Log\mathcal{L}(\mathbb{P}_{i,l,j|b}; y_{i,l,j}; \mathbb{P}_{i,b}; y^a_{i,b})$$

We again estimate the parameters numerically and the estimated parameter for the adoption cost represents the effect of this cost on the log-odds ratio for adoption, while the usage parameters enters nonlinearly the calculation of the expected utility of adoption, $u^a_{i,b}$. The log-odds ratio for any given bundle b' and b'', $b' \neq b''$, is given by

$$ln\left(\frac{\mathbb{P}_{i,b'}}{\mathbb{P}_{i,b''}} \right) = (u^a_{i,b'} - c_{b'}) - (u^a_{i,b''} - c_{b''}) = (u^a_{i,b'} - u^a_{i,b''}) + (c_{b''} - c_{b'})$$

Also in the adoption stage, the choice of adopting b' versus b'' does not depend on any other

alternative other than b' and b''.

In case of a binary bundle, i.e. cash only or cash and card in the wallet, we have

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card\}}}{\mathbb{P}_{i,\{cash\}}}\right) = (u^a_{i,\{cash,card\}} - u^a_{i,\{cash\}}) + (c_{\{cash\}} - c_{\{cash,card\}})$$

where $c_{\{cash\}} = 0$ and

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card\}}}{\mathbb{P}_{i,\{cash\}}}\right) = (u^a_{i,\{cash,card\}} - u^a_{i,\{cash\}}) - c_{\{cash,card\}}$$

In the multinomial case (triple bundle), i.e. cash only, cash and cards or cash, cards and applications in the wallet, we have (where $c_{\{cash\}} = 0$)

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card,app\}}}{\mathbb{P}_{i\{cash\}}}\right) = (u^a_{i,\{cash,card,app\}} - u^a_{i,\{cash\}}) - c_{\{cash,card\}} - c_{\{cash,card,app\}}$$

and

$$ln\left(\frac{\mathbb{P}_{i,\{cash,card,app\}}}{\mathbb{P}_{i,\{cash,card\}}}\right) = (u^a_{i,\{cash,card,app\}} - u^a_{i,\{cash,card\}}) - c_{\{cash,card,app\}}$$

Note that the estimated parameters enter nonlinearly the log-odds ratio for adoption through the expected utility $u^a_{i,b}$. Hence, the coefficients for the payment instrument attributes cannot be interpreted linearly as in the usage case. On the other hand, the adoption cost has a linear interpretation in the log-odds ratio equation for adoption. As in the usage stage, to get the estimated effects on the choice probabilities directly, i.e. to get the partial effects, we can reverse-engineer the log-odds ratio.

A3. Adoption utility

Consumer i selects the payment instrument from her bundle that delivers the highest utility

$$\max_{j \in b} \tilde{u}_{i,l,j}$$

Recalling that $\tilde{u}_{i,l,j} = \tilde{v}_{i,l,j} + \epsilon_{i,l,j}$ and that $\epsilon_{i,l,j}$ is Gumbel distributed, we can use the so-

called Gumbel trick. The cumulative distribution function of a maximum of random variables is given by

$$Pr\left(\max_{j \in b} \tilde{u}_{i,l,j} \leq t\right) = Pr\left(\tilde{u}_{i,l,j} \leq t, \ldots, \tilde{u}_{i,l,k} \leq t\right)$$

for each $j \neq k \in b$. Thanks to independence, substituting the definition of $\tilde{u}_{i,l,j}$ and the expression for the Gumbel cumulative distribution function, and after some algebra we have

$$\max_{j \in b} u_{i,l,j} \sim Gumbel\left(ln \sum_{j \in b} e^{\tilde{v}_{i,l,j}}, 1\right)$$

Being at the adoption stage, consumer i calculates the expected maximum utility she would get from using a payment instrument in a bundle. Now that we know the distribution of the maximum, we can calculate its expected value

$$\mathbb{E}_\epsilon\left(\max_{j \in b} \tilde{u}_{i,l,j}\right) = ln \sum_{j \in b} e^{\tilde{v}_{i,l,j}} + m$$

where m is the Euler-Mascheroni constant (omitted hereafter). Finally, at the adoption stage, consumer i calculates the gross (over all transactions) expected maximum utility from using a means of payment in a bundle

$$u_{i,b}^a = \sum_{l=1}^{L} \mathbb{E}_\epsilon\left(\max_{j \in b} \tilde{u}_{i,l,j}\right)$$

i.e.

$$u_{i,b}^a = \sum_{l=1}^{L} ln \sum_{j \in b} e^{\tilde{v}_{i,l,j}}$$

B. Tables

B1 Usage: Cash and card usage

VARIABLES	(1) Card/cash	(2) Card/cash	(3) Card/cash
Card usage benefit	-0.702***	-0.805***	-1.709***
	(0.020)	(0.123)	(0.135)
Acceptance	0.354***	0.246***	0.234***
	(0.017)	(0.017)	(0.018)
Transaction speed	0.414***	0.331***	0.355***
	(0.017)	(0.017)	(0.018)
Anonymity/privacy	-0.147***	-0.166***	-0.140***
	(0.022)	(0.023)	(0.024)
Ease of use	0.505***	0.372***	0.396***
	(0.017)	(0.017)	(0.018)
Safety	0.361***	0.317***	0.323***
	(0.017)	(0.018)	(0.019)
Convenience	0.429***	0.376***	0.442***
	(0.022)	(0.023)	(0.025)
Settlement speed	-0.196***	-0.245***	-0.250***
	(0.024)	(0.024)	(0.026)
Budgeting	0.440***	0.356***	0.365***
	(0.016)	(0.017)	(0.018)
Cash balance	N	Y	Y
Gender	N	Y	Y
Age	N	Y	Y
Country	N	Y	Y
Location	N	Y	Y
Education	N	Y	Y
Occupation	N	Y	Y
Income	N	Y	Y
Transaction size	N	N	Y
Transaction context	N	N	Y
Pseudo R2	0.046	0.090	0.169
N	67432	65671	65671

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Model for usage decision: structural random utility logit model. The outcome variable is a binary variable for card and cash usage. The control variables are the payment instrument attributes (whose coefficients are displayed) as well as consumer- and transaction-level characteristics (second and third columns). Standard errors, reported in parenthesis, are robust and clustered at the consumer level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Model fit: McFadden's pseudo R2.

Consumer adoption and merchant acceptance

	(1)	(2)
Conditional on	Adoption	Adoption and acceptance
VARIABLES	Card/cash	Card/cash
Card usage benefit	-0.543***	-0.374***
	(0.021)	(0.023)
Acceptance	0.347***	0.347***
	(0.017)	(0.019)
Transaction speed	0.388***	0.421***
	(0.017)	(0.019)
Anonymity/privacy	-0.168***	-0.180***
	(0.022)	(0.024)
Ease of use	0.483***	0.495***
	(0.017)	(0.019)
Safety	0.332***	0.381***
	(0.018)	(0.019)
Convenience	0.347***	0.385***
	(0.023)	(0.025)
Settlement speed	-0.190***	-0.223***
	(0.024	(0.026)
Budgeting	0.437***	0.463***
	(0.017)	(0.018)
Cash balance	N	N
Gender	N	N
Age	N	N
Country	N	N
Location	N	N
Education	N	N
Occupation	N	N
Income	N	N
Transaction size	N	N
Transaction context	N	N
Pseudo R2	0.041	0.047
N	67432	66329

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Model for usage decision conditional on adoption (first column) and adoption & acceptance (second): structural random utility logit model in which choice probabilities are zero if a consumer does not adopt an instrument (first column) and an instrument is neither adopted nor accepted (third). The outcome and control variables are the same as in column (1) of Table 1. Standard errors, in parenthesis, are robust and clustered at the consumer level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Model fit: McFadden's pseudo R2.

B2 Adoption: Bundle adoption

VARIABLES	(1) {App, card, cash}/{Card, cash}	(2) {App, card, cash}/{Card, cash}
	Adoption stage only	
App adoption cost	3.499***	3.484***
	(0.029)	(0.029)
	Usage and adoption stage	
Card usage benefit	-0.137***	0.052**
	(0.021)	(0.022)
Acceptance	0.361***	0.363***
	(0.024)	(0.026)
Transaction speed	0.437***	0.468***
	(0.024)	(0.026)
Anonymity/privacy	-0.600***	-0.634***
	(0.029)	(0.031)
Ease of use	0.539***	0.561***
	(0.024)	(0.026)
Safety	0.429***	0.469***
	(0.025)	(0.027)
Convenience	0.093***	0.120***
	(0.028)	(0.031)
Settlement speed	-0.559***	-0.587***
	(0.032)	(0.035)
Budgeting	0.524***	0.552***
	(0.023)	(0.025)
Cash balance	N	N
Gender	N	N
Age	N	N
Country	N	N
Location	N	N
Education	N	N
Occupation	N	N
Income	N	N
Transaction size	N	N
Transaction context	N	N
AIC	195701.5	177596.2
N	66865	65773

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Joint structural random utility logit model for usage and adoption decisions. Column (1) and (2) show the mobile-app adoption stage estimates when usage is constrained by adoption (1) and both adoption and acceptance (2). Parameters are estimated jointly across stages. The control variables are the same as in column (1) of Table 1. Standard errors, in parenthesis, are robust and clustered at the consumer level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Model fit: AIC.

Drivers of the adoption cost

VARIABLES	(1) {App,card,cash}/{Card, cash}
App adoption cost	3.750***
	(0.031)
Information discovery	-0.805***
	(0.121)
App diffusion	-0.064***
	(0.015)
Attributes	Y
Cash balance	N
Gender	N
Age	N
Country	N
Location	N
Education	N
Occupation	N
Income	N
Transaction size	N
Transaction context	N
AIC	195179
N	66756

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Drivers of the adoption cost $\mathbf{d}_i$: information discovery and mobile-apps diffusion. Standard errors, reported in parenthesis, are robust and clustered at the consumer level. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. Model fit: AIC.

Optimal CBDC design

Attribute	Best design	λ_{best}	Worst design	λ_{worst}
Acceptance	Cash	0	App	1
Transaction speed	App	1	Cash	0
Anonymity/privacy	Cash	0	App	1
Ease of use	App	1	App	0
Safety	App	1	Cash	0
Convenience	App	1	Cash	0
Settlement speed	Cash	0	App	1
Budgeting	Cash	0	App	1

Table 5: Attribute design. Best CBDC design (second and third columns) against the worst CBDC design (fourth and fifth columns).

C. SPACE 2022 Survey

C1. Survey description, scope and countries covered

The Eurosystem's Study on Payment Attitudes of Consumers in the Euro Area (SPACE) constitutes an extensive exploration into the transaction behaviour of euro-area inhabitants. The present paper uses data from the second iteration of this survey, conducted during the autumn of 2021 and spring of 2022 (SPACE 2022 survey), which builds upon the first iteration of the survey, which was conducted in 2019 (SPACE 2019 survey). Both the SPACE 2019 and SPACE 2022 surveys slightly differ from its 2016 predecessor, the Study on the Use of Cash by Households (SUCH).

The SPACE 2022 survey comprises a payment diary and supplementary questionnaire. The latter consists of modules covering POS payments for goods and services, person-to-person (P2P) transactions, online payments excluding regular bills, and recurring payments, such as rent and utilities.

Kantar Public, a market research firm, conducted the survey across 17 of the 20 euro-area countries, excluding Germany, the Netherlands[36] and Croatia (due to its non-membership at the time of data collection). Therefore, the SPACE survey includes Belgium, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Malta, Austria, Portugal, Slovenia, Slovakia, and Finland. The methodology and descriptive evidence discussed below refer to these specific 17 countries' data collection.

C2. Survey design: sample size and country representativeness

The SPACE 2022 survey engaged 40,269 participants aged 18 and above, and post-data cleansing, 39,766 interviews remained in the data. Country-specific sample sizes within the SPACE 2022 survey were predetermined to yield certain quantities of POS transactions, set at 2,000 for smaller countries, 4,000 for medium, and 8,000 for larger nations. These goals, coupled with the average number of POS transactions reported by a sample unit from SPACE 2019, were used to determine the target number of consumer respondents. The survey design additionally

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[36]For Germany and the Netherlands, the respective national central banks conducted separate surveys with a questionnaire that was harmonised with SPACE. For this reason, data for these countries are not available.

integrated quotas related to gender, age, and the day in which transactions were recorded, to ensure robust demographic representation and balanced week-long data. Surveillance of regional residency and educational breakdowns of respondents was maintained throughout the fieldwork stages to maintain representative sampling along these dimensions.

The survey used a mixed-mode approach, integrating computer-assisted telephone interview (CATI) and computer-assisted web interview (CAWI) methodologies, with each country's sample evenly divided between the two. The CATI sample was probabilistic, employing random digit dialing (RDD) for selection, ensuring all euro-area citizens had a non-zero probability of selection. However, the CAWI sample, drew from a non-probabilistic frame, with Kantar Public online panels serving as the primary source. The survey execution occurred in two rounds, first from October to December 2021, and the second from March to June 2022, with a deliberate spacing to counteract potential seasonal effects on payment behaviours. The first and second rounds were allocated 40% and 60% of the sample share, respectively, to achieve uniform pacing across countries and modalities.

C3. Validation and weighting

The SPACE 2022 survey data used in this paper has been validated. Data validation after fieldwork entailed a comprehensive examination of responses for completeness, consistency, and plausibility against several criteria, including sociodemographic factors, outliers, inconsistent or unusual answers, diary balance, and congruity between respondent characteristics and reported payments. Based on predetermined guidelines, flagged inconsistencies facilitated data cleansing and outlier identification. Each respondent had 54 flag variables for logical checks, and a total of 1.2% of the initial interviews were consequently discarded due to inconsistencies. In addition, outlier detection for specific variables led to the imputation of inconsistent or unplausible values and non-responses, using the k-nearest neighbours (KNN) method. The overall aggregates calculated from the responses of the SPACE 2022 were subsequently contrasted with the SPACE 2019 results for additional validation.

The data was weighted to minimise survey estimate bias and ensure accurate inferences based on the demographic characteristics of each country. The weighting procedure consisted of three

steps. Initially, the offline respondent net sample was weighted according to established population benchmarks, with the probability-based telephone sample serving as the primary weighting source. Subsequently, the online sample was harmonized with the weighted probabilistic sample of internet-accessing respondents using several balancing variables, both demographic and topic-specific. Finally, the online and offline respondents were merged and the combined data was weighted according to the same population benchmarks. This procedure improved differences in key outcomes between the online and telephone samples, but could not eliminate them entirely due to likely modal differences and possible unobserved variations in sample profiles.

C4. Definitions of payment instruments and transaction types

The SPACE 2022 survey explores a range of payment instruments, including cash (physical paper currency), cards (broad category including various card types, such as debit cards, credit cards, and prepaid cards) and mobile phone applications (broad category including bank-provided apps, mobile wallets, such as Apple Pay or Google Pay, apps enabling instant payments, and other mobile applications facilitating payments). The survey also records transactions made by the bank cheque, credit transfers (electronic movement of funds from one bank account to another, including via online banking platforms) and other instruments, such as loyalty points, vouchers, and gift cards.

The classification of transaction types in the SPACE 2022 entails POS payments, P2P payments, online payments and recurring payments. POS payments cover payments at physical locations, such as supermarkets, day-to-day shops, service providers, venues for cultural or sporting activities, and more. P2P payments include non-commercial transactions between individuals, including categories such as donations or payments to family members or friends. In terms of online payments, SPACE 2022 focuses only on non-recurring online payments and excludes 'Cash' and 'Bank cheque' as payment options. SPACE 2022 also includes recurring payments defined as the regular payments consumers make, such as rent and utility bills, although these type of payments are outside the scope of this paper.

C5. Summary statistics

This section provides a descriptive analysis of relevant data from the SPACE 2022 survey, examining consumers' preferences for the different attributes of cash and cards, payment behaviours across sociodemographic characteristics, countries, and transaction characteristics. Additionally, it illustrates variables identified in the main text as potential proxies for the adoption of payment instruments, such as card ownership and preferences for card and mobile payments.

Attribute preferences for cash and cards

Consumers were asked for up to three main advantages of for cash and cards. The list of payment instrument attributes are included in Table 6.

	Attribute	Card	Cash
1	Perceived acceptance	0.22	0.30
2	Transaction speed	0.43	0.17
3	Anonymity/Privacy	-	0.38
4	Ease of use	0.41	0.19
5	Safety	0.29	0.17
6	Convenience	0.59	-
7	Settlement speed	-	0.29
8	Budgeting	0.19	0.38

Table 6: Preferences for payment method attributes. The reported values represent fraction of 31,163 distinct consumers who selected each of the attribute. The survey design allowed respondents to select up to three most important attributes for each payment instrument.

The columns "Cash" and "Cards" of Table 6 indicate the fraction of 31,163 unique respondents from the SPACE survey who considered each attribute important for cash and cards. Avoiding the carrying cost of cash ('Convenience') was deemed the most significant advantage for card use, with 59% of consumers selecting this unique card attribute. Conversely, 'Anonymity/privacy' and 'Settlement speed' are exclusive benefits identified with cash, recording preferences of 0.38 and 0.29, respectively. 'Budgeting' is also perceived as an important advantage of cash, with a preference rate of 0.38. 'Transaction Speed' and 'Ease of use' are also key perceived strengths of cards, with consumer preference rates of 0.43 and 0.41, respectively, compared to cash's lower rates of 0.17 and 0.19. Attributes like 'Perceived Acceptance' and 'Safety' show more balanced preferences between the two payment instruments.

Use of payment instruments at the POS in transaction volume, by sociodemographic factors

Sociodemographic factors. In the SPACE 2022 survey, several critical sociodemographic factors were recorded. The salient categories explored in the survey include gender, age, education, income, rurality, and occupation. In Table 7, each of these demographic variables was cross-tabulated with the respondents' choice of payment method: cash, card, mobile, and other forms of payment. The results of this table are also depicted in Figure 11.

Among the gender category, both males and females showed a higher inclination towards cash, with 57% of men and 55% of women using this method at the POS. Card payments followed as the second most popular choice across all genders. For all age groups, cash remained the most used payment method, followed by cards though mobile payments are slightly higher among younger demographics. Education level presented interesting trends: among those with primary education, 64% of transactions were paid with cash, and as the educational attainment increased, there was a noticeable shift towards card payments, with the highest-educated group (PhD or equivalent) displaying a share of 40% of all transactions. Income levels were also a determinant of payment choice, with lower income brackets paying more with cash, but as income increased, a tendency for card payments emerged. At the highest income bracket, 51% of payments where conducted using cards.

The place of residence, either rural or urban, did not seem to significantly influence payment preferences, with cash being dominant in both cases. Occupation-wise, all groups tended to favor cash payments, with employees slightly more likely to use card payments compared to self-employed individuals and the unemployed or students.

	Cash	Card	Mobile	Other
Gender				
Male	0.57	0.36	0.04	0.03
Female	0.55	0.38	0.03	0.04
Age				
18-24	0.53	0.36	0.06	0.04
25-39	0.52	0.40	0.05	0.04
40-54	0.56	0.37	0.04	0.03
55-64	0.59	0.36	0.02	0.03
65+	0.59	0.36	0.02	0.03
Education				
Primary	0.64	0.31	0.02	0.03
Lower secondary	0.61	0.35	0.02	0.03
Upper secondary	0.58	0.35	0.03	0.03
Post-secondary	0.56	0.37	0.03	0.03
University	0.51	0.41	0.05	0.04
PhD or equivalent	0.53	0.40	0.03	0.03
Income				
<€500	0.62	0.30	0.03	0.05
€501-€1000	0.60	0.32	0.03	0.05
€1001-€2000	0.60	0.34	0.03	0.03
€2001-€3000	0.58	0.36	0.03	0.03
€3001-€4000	0.53	0.40	0.03	0.03
€4001-€6000	0.45	0.47	0.05	0.03
>€6000	0.39	0.51	0.06	0.03
Rurality				
Rural (-50k inhabitants)	0.54	0.40	0.03	0.03
Urban (50k+ inhabitants)	0.57	0.36	0.04	0.03
Occupation				
Self-employed	0.59	0.33	0.04	0.03
Employee	0.53	0.40	0.04	0.04
Unemployed or student	0.59	0.36	0.02	0.03

Table 7: Use of different means of payments at the point of sale (POS), by sociodemographic factors.

Country results. The SPACE 2022 survey shows varying transaction behavior across different countries. Figure 12 reflects the proportion of transactions conducted through cash, card, mobile, and other means in various countries. In Austria, Italy, and Slovenia, the majority of transactions were conducted with cash, accounting for 67%, 68%, and 72% of transactions respectively. Similarly, in Spain and Portugal, cash transactions represented 65% and 64% respectively. On the other end of the spectrum, Finland had the lowest reliance on cash, with just 20% of transactions, with the majority, 69%, conducted via card. Luxembourg and Estonia also had card transactions dominating, with shares of 52% and 51% respectively. Mobile transactions had a minor, but notable share across all countries. Finland exhibited the highest usage at 7% of transactions. The lowest usage was in Slovenia, where mobile transactions made up just 1% of the total.
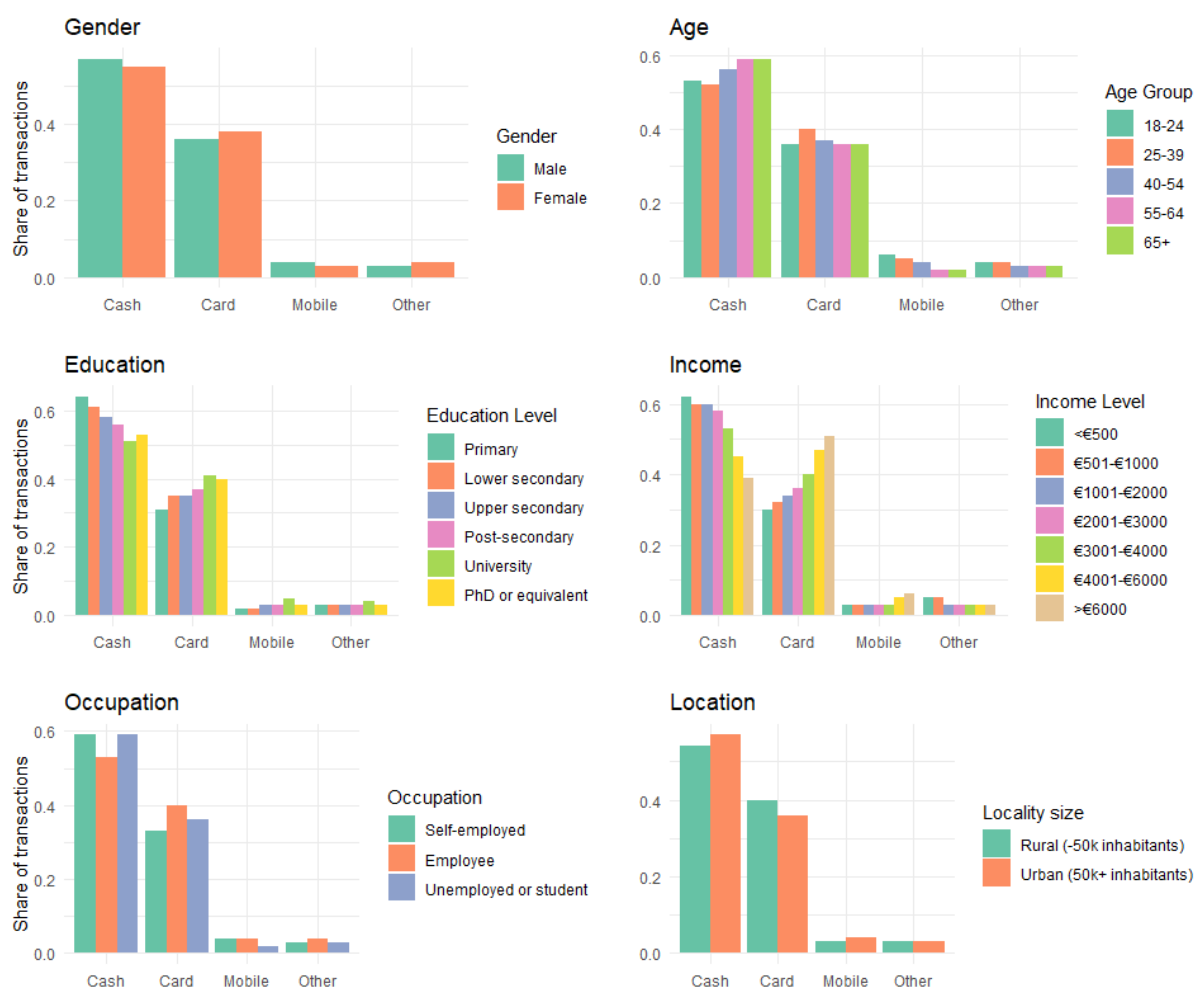
Figure 11: Share of transactions, by sociodemographic factors

Payment location. Transaction characteristics are generally underscored as relevant determinants of payment behaviour. Drawing on the transaction data gathered by the SPACE 2022 survey, Figure 13 depicts payment instrument usage across different payment locations. Analysing the share of transactions, one can observe variations in the usage patterns of cash, cards, and mobile payments in various retail environments. Supermarkets see a relatively balanced utilisation of cash and cards, with 52% and 41% of transactions respectively, but a modest 3% share for mobile payments. Shops for day-to-day items lean more towards cash, which constitutes 60% of transactions, in contrast to cards at 35%. Cash also maintains a strong presence in restaurants, bars, and cafes, accounting for 60% of transactions. For shops selling durable goods, a near parity exists between cash and card transactions at 47% and 46% respectively. At
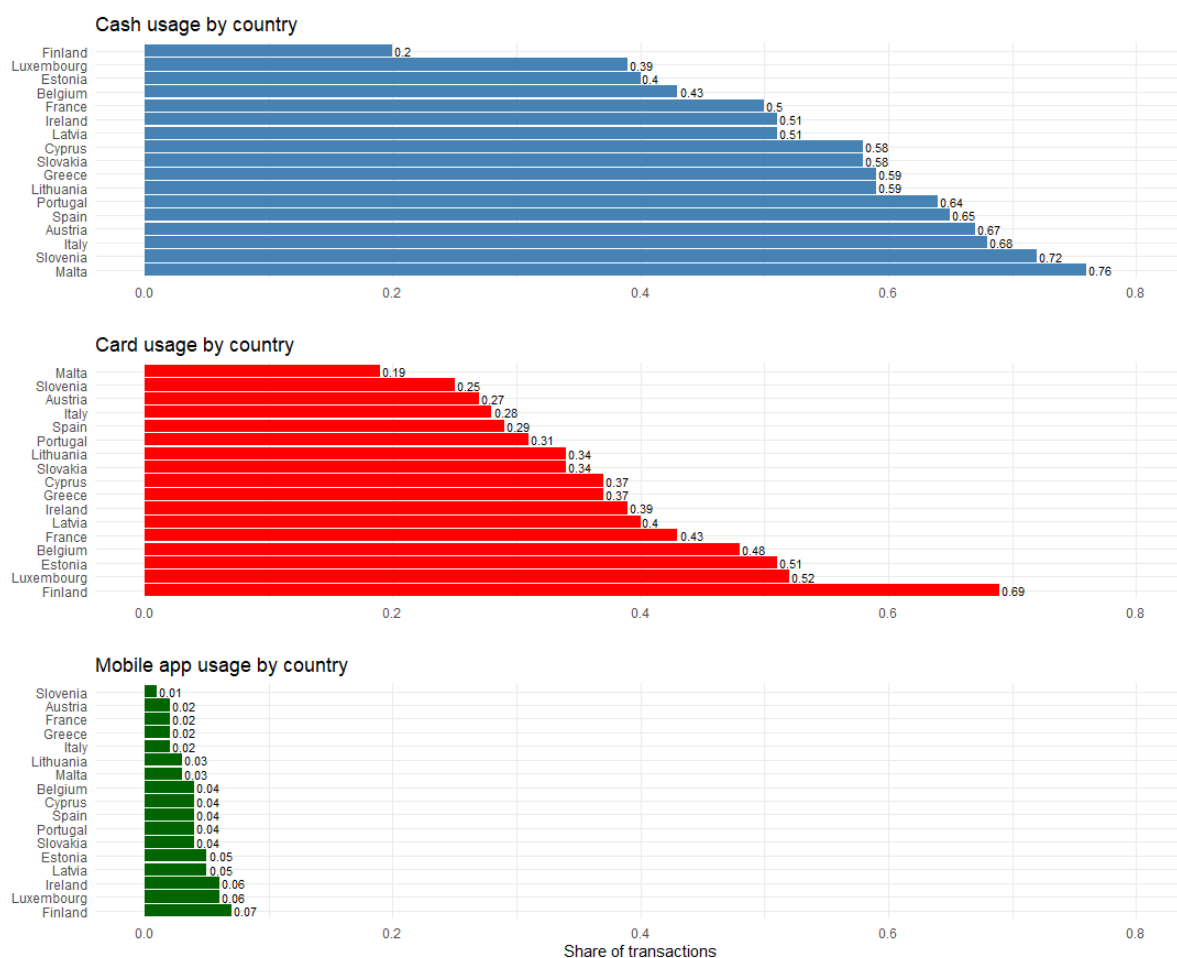
Figure 12: Share of transactions, by country

entertainment venues, cash also predominates with a 55%, while cards represent a 35% and the mobile payment share is at 5%.

Transaction size. Another important transaction characteristic is the transaction amount or size of the purchase. Relationship between transaction sizes and the choice of payment instrument, primarily cash and cards, as represented through a heatmap in Figure 14. The heatmap conveys an inversely proportional relationship between transaction size and the propensity for cash transactions, as observed in other payment surveys. As transaction values increase, the inclination towards cash transactions decreases. For example, in the lower transaction size interval of €0-€5, a substantial 79.2% of transactions were conducted in cash. As transaction size increases to the €5-€10, €10-€15, and €15-€20 ranges, the prevalence of cash transactions
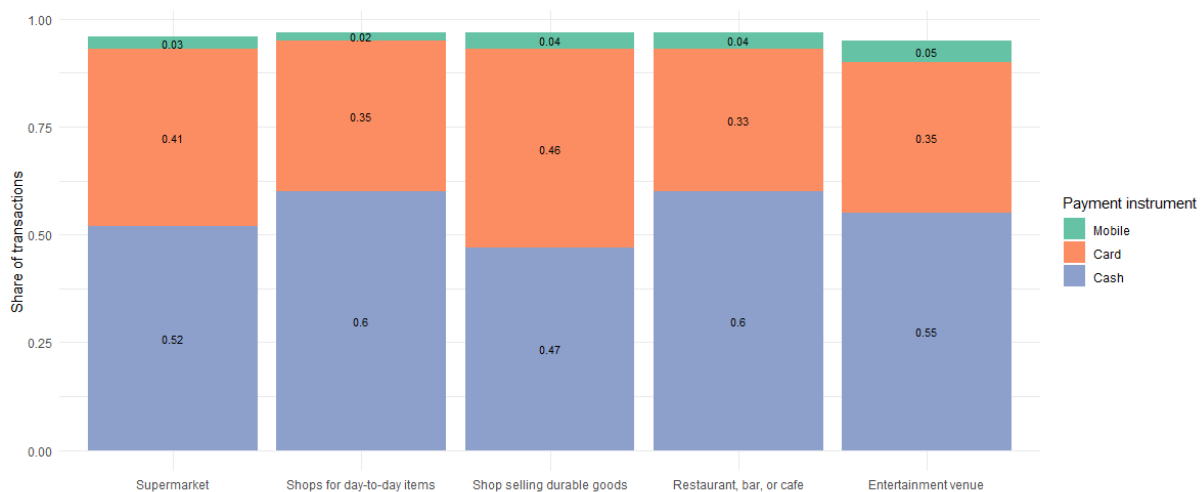
Figure 13: Share of transactions for different payment instruments, by payment location

sees a slight decline, accounting for 69.6%, 63.6%, and 56.7% of transactions, respectively. The contraction in cash transactions becomes more pronounced for larger transaction sizes. For example, for transactions ranging between €25 and €30, cash represents 51.1% of the total, and 50.3% for transactions within the €30-€40 range. As we approach transaction sizes exceeding €100, the frequency of cash transactions is noticeably reduced. In summary, SPACE 2022 data seems to mirror established observations of cash typically being the instrument of choice for low-value transactions.

Figure 14: Share of transactions, by transaction size

Cash balances. The interplay between consumers' cash balances in their wallets and transaction behaviour at the point of sale has also been explored in the literature. With data presented again in the form of a heatmap in Figure 15, the intensity of color denotes the share of transactions undertaken with either cash or cards across various cash balance intervals. As usually

observed in other payment surveys, there is a relationship between cash balances and cash transactions. For consumers holding low cash balances, for example between €0 and €25, the use of cash is relatively balanced with cards, as shown by a 44.3% share of cash transactions. However, for balances between €25-€50, the cash transaction share rises markedly to 60.5%. In the €50-€75 interval, it further escalates to 64.6%. The trend continues unabated in the €75-€100, €100-€150, and €150-€500 balance intervals, with the share of cash transactions standing at 66.6%, 67.2%, and 69.0% respectively. Interestingly, the €500-€1000 cash balance interval reflects a minor reduction in cash transaction share to 67.4%. Yet, consumers with significant cash balances between €1000 and €5000 exhibit a distinct shift in their transaction behaviour, with cash transactions representing a smaller share of 60.1%. For the rare instances of cash balances exceeding €5000, cash transactions increased to a 77.8%.
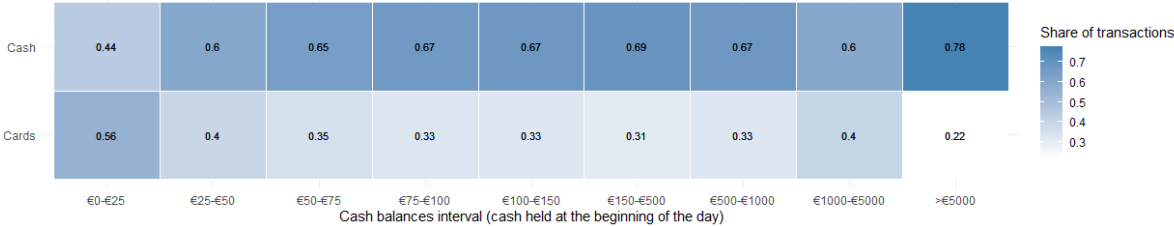
Figure 15: Share of transactions, by cash balances

Variables considered as cashless adoption proxies

The potential proxies for the adoption of cashless transactions discuss in the main text are card ownership, self-reported preference for cards, and self-reported preference for mobile payments.
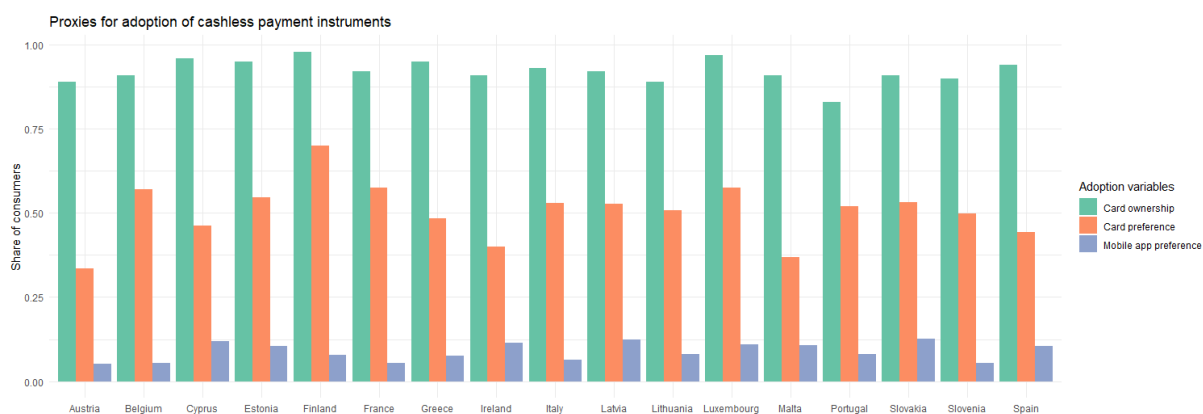
Figure 16: Share of consumers owning cards, preferring cards, or preferring mobile payments, by country

As indicated in the main text, Figure 16 shows that card ownership may not serve as an good proxy, due to its overwhelming prevalence, thus lacking the necessary variation to discriminate differences in consumer behavior. This is especially the case for the purposes of this paper which aims to simulate the adoption of CBDC which would be a new means of payment. An alternative proxy can be found in the self-reported preference for different cashless methods. When considering these preferences, it is noteworthy that our analysis adopts a broad preference definition, rather than a strict one. Specifically, we also account for consumers who express indifference between cash and cashless payment options but nonetheless show a preference for a particular cashless method. In this light, the card preference column represents the share of consumers indicating a preference for card payments, inclusive of those indifferent between cash and cashless transactions. This survey data indicates significant cross-country variation in card preference, with proportions ranging from a low of 33.4% in Austria to a high of 70.0% in Finland. On the other hand, the proportion of consumers showing preference for mobile payments is considerably smaller, peaking at 12.5% in Slovakia and remaining below 12% in all other countries. Hence, both the stated preference for cards and for mobile payments serve as more discriminative proxies of cashless adoption, especially for the case of mobile payments whose preference and usage are still low and could provide more insights regarding CBDC adoption.

When considering these preferences, it is important to highlight the inclusion of indifference

within our definition of 'preference'. Under our broad preference concept, not only strict preference for cash and cashless are included. Consumers who express no clear choice between cash and cashless payment options, yet still show a preference for a particular cashless method, are also counted as part of the preference group. This interpretation increases the percentage of consumers strictly favoring a specific cashless method. Figure 17 presents a more nuanced landscape of payment preferences, in which 51.95% of consumers favour cards over both cash and apps, with an additional 18.84% preferring cards over apps, but indifferent between cards and cash. Hence, 70.79% of consumers have a card-oriented preference when considering cashless options. Mobile apps are favored by a combined 10.17% of consumers, and a portion amounting to 19.03% of consumers express an unequivocal preference for cash.

Figure 17: Preference breakdown of consumers, including indifference between cash and cashless

C6. Selected questions

Usage of cash and cards

For $l \in \{1, \ldots, 8\}$, if reported an amount in QA5Al, ask QA7Al. Otherwise, move to QA9A.

- QA7Al. How did you make the lth payment?

    1. Cash

    2. Card (e.g. debit card, credit card or prepaid card)

    3. Mobile phone app

    4. Bank cheque

    5. Credit transfer (also via online banking)

    6. Loyalty points, vouchers and gift cards (e.g. Amazon or iTunes gift cards)

    7. Other

Payment instrument attribute preference

- QQ13a. For you personally, what are the three most important advantages of cash as compared with card payments? Cash payments...(MAX 3 ANSWERS)

    1. are accepted in more situations

    2. are faster

    3. are anonymous / protecting my privacy better

    4. are easier

    5. are safer

    6. are immediately settled

    7. make me more aware of how much I'm spending

    8. Other

    9. I do not use cash

    10. None

    999999. Don't know

- QQ13b. For you personally, what are the three most important advantages of card payments compared with cash? Card payments...(MAX 3 ANSWERS)

    1. are accepted in more situations

    2. are faster

    3. are easier

    4. are safer

    5. mean I don't have to worry about carrying enough cash

    6. make me more aware of how much I'm spending

    7. Other

    8. I do not use/have access to card payments

    9. None

999999. Don't know

Consumer adoption

- QQ1A (Card ownership). Which of the following do you have?

    1. An account from which you can make payments

    2. Card (debit card or credit card)

    3. Crypto-assets also known as crypto-currency (virtual assets, e.g. Bitcoin, Ethereum)

    4. None

    5. Don't know/refusal

- QQ3 (Cashless preference). If you were offered various payment methods in a shop, what would be your preference?

    1. Cash

    2. Card or other cashless payment

    3. I have no clear preference between cash and cashless payment

    4. Don't know

If respondent have cashless payment preference (QQ3 = 2 or 3), ask QQ3A.

- QQ3A (Mobile applications preference). Which of these payment methods do you prefer?

    1. Card (debit, credit)

    2. Mobile payments (including wearables like smartwatches)

    3. Bank cheque

    4. Don't know

- QQ19A (COVID-19 pandemic effect). Compared with the situation two years ago before COVID-19, are you using cash instead of non-cash payment methods more or less often for your payments in physical locations (shops, restaurants, etc.)?

    1. Much more often

2. Somewhat more often

3. The same as before

4. Somewhat less often

5. Much less often

6. Don't know

If respondent uses cash less often since COVID-19 (QQ19A=4 or 5), ask the following

- QQ19C (Reasons for switching behaviour). Which of the following reasons best explain why you now make cash payments less often than before the coronavirus pandemic?

    1. I cannot withdraw cash as easily as before the pandemic

    2. The fear of being infected by the virus

    3. The places where I buy goods or services no longer accept cash

    4. The places where I buy goods or services strongly advise not to

    5. The government recommended the use of cashless payments

    6. Paying electronically has been made more convenient

    7. I discovered other means of payment

    8. Other reasons

Merchant acceptance

For $l \in \{1, \ldots, 8\}$, if respondent paid in cash (QA7Al=1), ask QA8Al

- QA8Al. Were other payment methods such as card or mobile payment accepted?

    1. Yes

    2. No

    3. Don't know

If respondent did not pay in cash (QA7Al=2 through 7), ask QA8AIl.

- QA8AI*l*. Was cash accepted?

    1. Yes

    2. No

    3. Don't know

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