Online Appendix to

Cash or card? A structural model of payment choices

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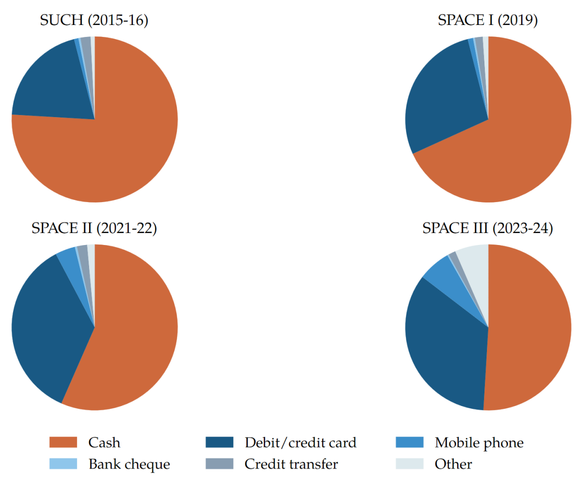
A Empirical appendix

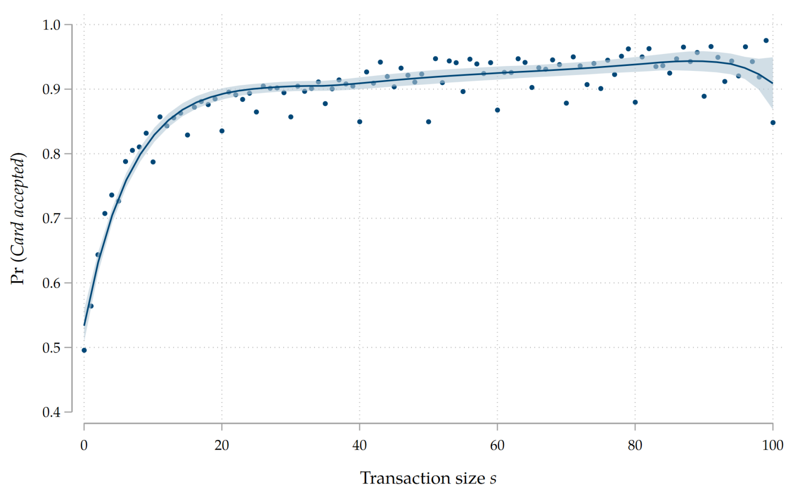
A.1 ECB payment diaries - additional figures

FIGURE A.1: Payment methods usage in different waves.



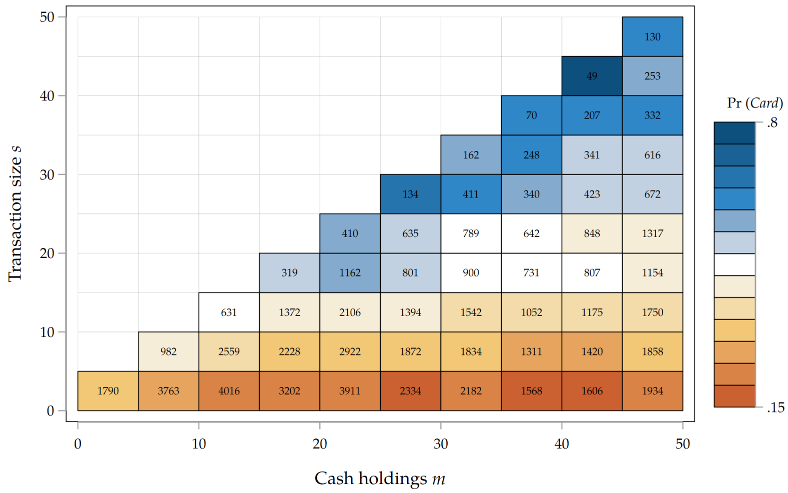
Note: This plot shows the share of transactions settled with each payment method across the three waves. Credit and debit cards are bundled together for comparability, as in the first wave of SPACE it was not asked if the payment card used was a debit or a credit card.

FIGURE A.2: Card acceptance for different transaction sizes s



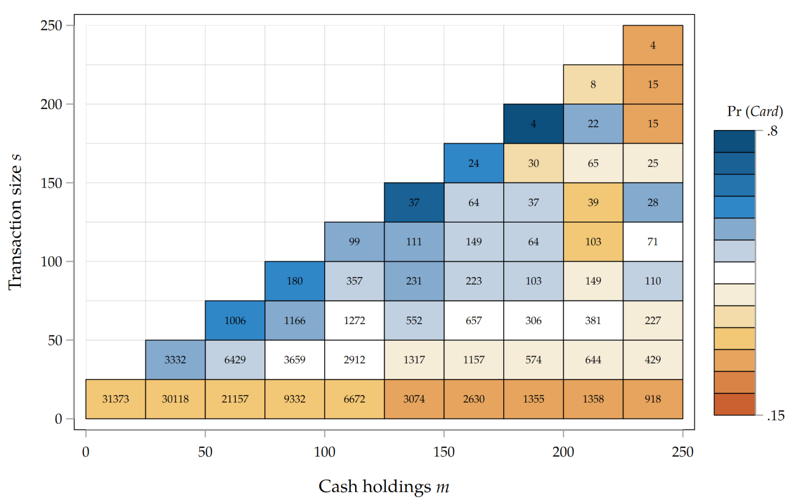
Note: Transaction sizes are rounded to the closest integer. For each binned transaction size, we plot the share of payments for which card payments were accepted at the point of sale. A third degree polynomial fit is overlaid to the plot.

FIGURE A.3: Share of cash payments for different m and s. Zooming in on smaller transactions/cash holdings levels.



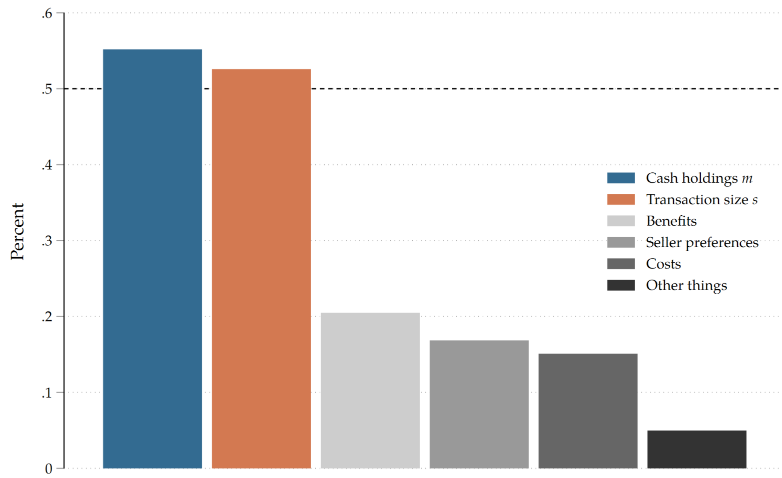
Note: The Figure displays the share of payments settled using cards for bins defined in terms of cash holdings at payment (m) and transaction size faced (s). Numbers denote the number of observations falling in each bin. We focus on transactions where m and s are smaller or equal than 50 euros.

FIGURE A.4: Share of cash payments for different m and s. Including larger transactions and cash holdings.



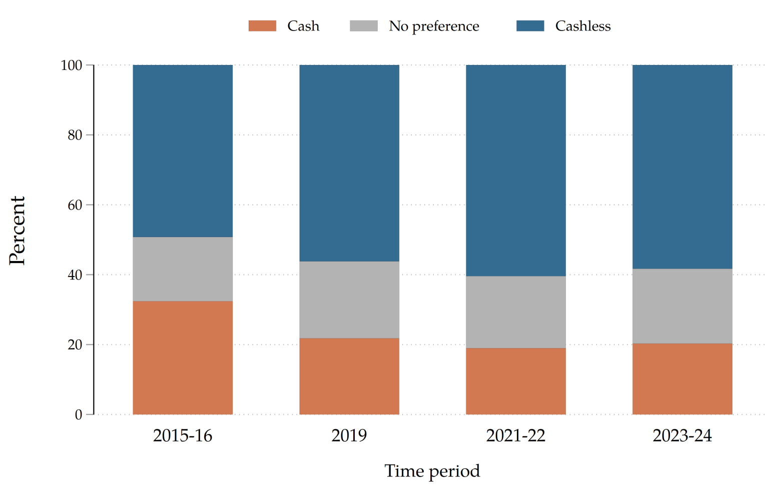
Note: The Figure displays the share of payments settled using cards for bins defined in terms of cash holdings at payment (m) and transaction size faced (s). Numbers denote the number of observations falling in each bin. We focus on transactions where m and s are smaller or equal than 250 euros.

Figure A.5: Reported determinants of payment method decisions.



Note: This graph displays the shares of households reporting that a certain factor influences their payment decision. The question respondents answered was: *"Which of the following influences your decision to pay with cash or card or other non-cash payment methods?"*. Multiple responses are possible. *Source: ECB SUCH (2016) Data.*

Figure A.6: Payment preferences over the years.



Note: This Figure shows the yearly distribution of answers to the question "If you were offered various payment methods in a shop, what would be your preference?".

A.2 Payment choice sets in SUCH and SPACE data

We now describe how to construct transaction-level *payment choice sets* using the SUCH and SPACE payment diary data, distinguishing between *forced cash*, *forced card*, and *unforced* payments.

The ECB payment diaries do not record cash balances at the exact time of each transaction. Let m_{it} denote the amount of cash held by individual i immediately before her tth transaction, and let s_{it} denote the corresponding transaction size. Cash holdings at payment are reconstructed starting from reported cash balances at the beginning of the diary day and updating them using information on cash withdrawals, cash receipts, and cash payments recorded during the day.

Two data limitations require additional discussion. First, for almost all respondents (with the exception of few participants in the SUCH survey which were explicitly asked) the exact timing of cash replenishments is not observed. In these cases, the timing of withdrawals can be inferred, to some extent, whenever a cash payment would otherwise violate the feasibility condition $s_{it} \leq m_{it}$. Purchases for which we could not uniquely reconstruct cash holdings at the time of the transaction were flagged, and excluded from all analyses at the transaction level. Second, we don't have information on the presence and timing of cash deposits during the diary day. We therefore compute predicted end-of-day cash balances assuming no deposits and compare them with reported end-of-day balances; observations implying unreported deposits or negative cash balances at any point during the day were dropped.

We excluded online payments and restricted the sample to respondents with access to at least one payment card. After applying these restrictions, the final sample includes a total of 338,773 transactions (carried out with either cash or cards) performed by 184,565 individuals.

For each purchase for which we are able to pin down cash balances at the time of the transaction, we determine the payment choice set (which payment methods were feasible) as follows. Cash is feasible if the transaction size does not exceed available cash holdings ($s_{it} \leq m_{it}$) and if the merchant accepts cash.[1] Card payments are feasible if the merchant

[1] In the SUCH survey, respondents were not asked if cash was accepted at the store. We therefore assume that cash was always accepted by merchants in 2015-16, which is consistent with the near-universal levels of cash

accepts at least one card-based payment instrument and the respondent owns a debit card, a credit card, or both. Since the data do not identify which specific types of cashless payment methods are accepted at each transaction, we assume that debit and credit cards are accepted whenever respondents report that cashless payments were accepted at the store, while we consider the access to other cashless instruments (e.g., cheques or credit transfers) as not sufficient to guarantee the feasibility of a card payment.

A transaction is classified as *unforced* if both cash and card payments are feasible. Otherwise, the transaction is classified as either *forced cash* or *forced card* depending on which payment method is available. For some transactions, we cannot pin down the payment choice set even if we observe m_{it} with certainty: this happens when (i) the size of the transaction s_{it} is missing, or (ii) the respondent did not state whether the alternative payment method (with respect to the one they used) was accepted.

A.3 Payment choices: regression analysis

In this Subsection, we test if the descriptive findings of Section 2 of the main text are robust to a more sophisticate analysis. In principle, it could be that patterns emerging in Figure 2 of the main text are entirely due to selection: for instance, it might be that households who generally prefer to use cards have on average lower cash holdings, or that they buy more valuable goods. As our data contains multiple transactions per individual, we can rule out these potential issues by relying on fixed effects models. In particular, we want to assess whether i) higher s increases the probability of a cashless payment, ii) higher m decreases the probability of a cashless payment; iii) the effects of a rise in s is stronger when m is smaller

acceptance observed in the earlier SPACE waves.

Table 1: Regression evidence on the joint importance of m and s.

Unit: EUR 100	Dependent variable: $PayCard_{it}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cash holdings m	-0.11***	-0.098***	-0.037***	-0.058***	-0.052***	-0.050***	-0.0038	-0.020***
	(0.0014)	(0.0014)	(0.0018)	(0.0022)	(0.0017)	(0.0017)	(0.0022)	(0.0025)
Payment size s	0.61***	0.47***	0.31***	0.41***	0.79***	0.62***	0.54***	0.68***
	(0.0040)	(0.0042)	(0.0077)	(0.0076)	(0.0060)	(0.0060)	(0.012)	(0.012)
Cash holdings m $\times$ Payment size s					-0.20***	-0.16***	-0.15***	-0.18***
					(0.0047)	(0.0044)	(0.0060)	(0.0063)
Observations	251427	229694	137183	150839	251427	229694	137183	150839
Unforced			✓	✓			✓	✓
Controls		✓	✓			✓	✓	
Random effects				✓				✓
Robust SEs	✓	✓	✓	✓	✓	✓	✓	✓

Note: Columns (2-3) and (6-7) include controls such as country, survey year, sex, age group, education and income of respondents, type of store. Columns (3-4) and (7-8) only take into account unforced transactions, i.e., transactions where both payments methods were available for the respondent. Columns (4) and (8) include individual-level random effects. Heteroskedasticity-robust standard errors are reported.

and viceversa, as m' matters for choices. [2] We estimate linear probability models of the form

$$PayCard_{it} = \beta_0 + \beta_s s_{it} + \beta_m m_{it} + \beta_{sm} \left(s_{it} \times m_{it} \right) + \lambda' \mathbf{X}_{it} + \zeta_i + \varepsilon_{it}, \tag{1}$$

where $PayCard_{it} = 1$ $(= 0)$ if individual i settles her $t-$th transaction using cashless methods (cash), $\mathbf{X}_{it}$ denote transaction-specific characteristics and ζ_i denote individual-level fixed effects.

The results are displayed in Table 1. Models (1) to (4) are intended to test whether card usage probabilities are increasing in the transaction size s and decreasing in the amount of cash holdings m. Our preferred specification (column (4), where we focus on unforced transactions and we include individual-specific random effects) reveals that a EUR 10 increase

[2] To test if choices are affected by m', we can estimate whether the effect of s is different according to the level of m. If s only affects choices through perceived cost/benefits of using cash instead of cards (for instance, because there are proportional fees, or because agents dislike paying small sums using their card as they perceive that merchants prefer them to pay cash), the effect of s should be independent of m, as long as $s \leq m$. At the same time, if agents care about the level of m because they want to get rid of cash they have, the effect of m shouldn't depend on s, as long as $s \leq m$. The presence of a significant interaction term points towards the existence of a more complex relationship between s, m and choices, which would be consistent with the story suggested by the previous two Figures. If households don't want to run out of cash, higher s increases the probability of cashless payments, but the effect of s is smaller as m grows. At the same time, higher m decreases the probability of a cashless payment, and it decreases it more when s is larger (as one abandons the region when $m - s \simeq 0$).

in cash holdings m is associated with 0.6pp decrease in the probability of paying by card. The opposite is true for the transaction size: a 10 EUR increase in s is associated with a 4.1pp rise in the probability of card usage. Models (5) to (8) are instead meant to test the whether choices are really driven by $m' = m - s$. In order to do so, we can estimate whether the effect of m changes depending on the level of s. In particular, if agents really want to avoid running out of cash, thereby increasingly relying on cards as $m' \to 0$, we should find a negative coefficient on the interaction between cash holdings and payment size[3]. The estimated coefficient is indeed negative and statistically significant, corroborating our descriptive analysis. In particular, we find that the probability of a card payment decreases by 3.2pp for a EUR 10 increase when the payment size $s$is close to zero, but the marginal impact of cash holdings becomes stronger as the transaction size rises: for instance, for a EUR 50 payment, having 10 more euros on hand is associated with an extra probability of paying with cards of 4pp. Similarly, notice that the effect of payment size decreases as m rises, and even turns negative for sufficiently high cash holdings. Notice that this is consistent with optimal cash holdings being finite: if agents optimally want to hold a quantity of cash m^*, for $m > m^*$ they will increasingly use cash as s increases, as when cash holdings are very high, large payments can be exploited to bring cash holdings closer to their optimal value.

A.4 The role of imperfect card acceptance

The evidence of Section 2 of the main text shows that households prefer to avoid having too little cash and therefore use cards when doing otherwise would result in a near depletion of their cash balances. This suggests the existence of a precautionary motive to hold a buffer stock of cash. A possible driver of such precautionary motive is avoiding situations in which cash balances are too low to carry out a transaction, especially if there is a significant risk that cards are not accepted at the point of sale. There are two ways to avoid little cash on hand: agents can either use cards when s is very close to m or visit ATMs way before they reach $m = 0$. Our data enables us to understand if the households' precautionary motive for holding cash is driven (at least to some extent) by imperfect card acceptance. We do this

[3]If households do not want to run out of cash, higher s increases the probability of card payments, but the effect of s is smaller as m grows. At the same time, higher m decreases the probability of a card payment, and it decreases it more when s is larger (as one abandons the region when $m - s \simeq 0$).

by splitting the sample in two groups of households according to the card acceptance rate they are exposed to.[4] Figure A.8 shows how the payment choices and cash management of these two groups of households differ in the ways we hypothesized above. In the left panel, we display a split-sample version of the right panel of Figure 2 of the main text. The Figure shows that the probability of using cards rises as $s \to m$ especially for households exposed to low acceptance rates; in other words, imperfect acceptance is at least partially driving the rise in the probability of card usage as $s \to m$ we described in Section 2 of the main text. In the right panel of Figure A.8, we display the probability of performing a cash withdrawal before the next purchase as a function of current cash holdings m, for the two groups of households: the graph shows that for households exposed to lower card acceptance rates the probability of withdrawing cash spikes up when m is low, while this does not apply to households exposed to high card acceptance. Taken together, the two plots suggest that households want to hold low amounts of cash when card acceptance is far from being universal, since being matched with a non-accepting vendor in those circumstances would lead to either i) the impossibility to carry out the desired transaction, or ii) the need to rush to an ATM before going back to the store and completing the purchase.

[4]Expected acceptance rates are predicted probabilities derived from a logistic regression with demographic and geographical controls. Details are available upon request.

Figure A.7: Payment size distribution (EUR, logs)

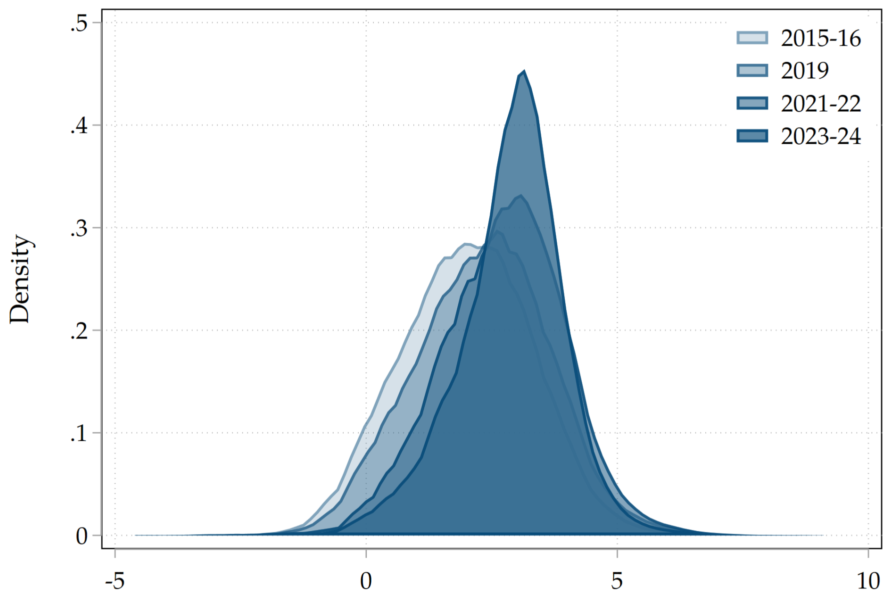
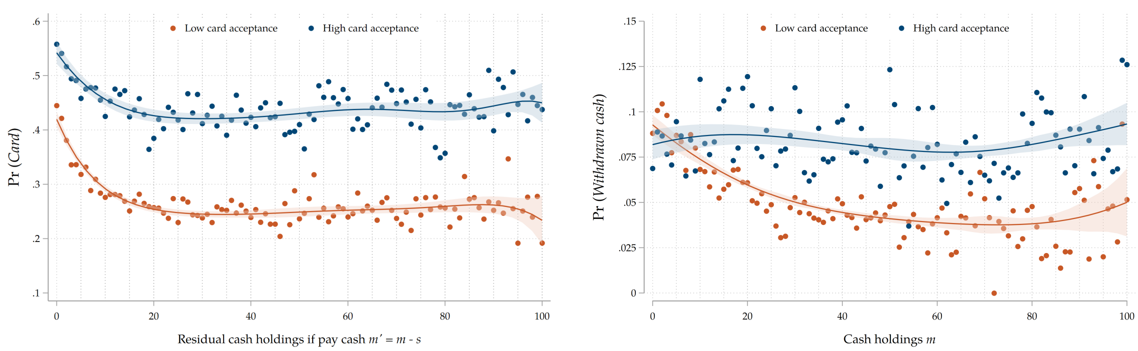


Figure A.8: Card acceptance, payment choices and cash management.



Note: The left panel displays the shares of households paying using cards for bins defined in terms of cash holdings remaining in case agents settle the payment using cash (*implied residual cash holdings* $m' = m - s$), for two groups of individual respectively exposed to a card acceptance rate lower (higher) than the median one. Only unconstrained transactions are considered, and transactions with $m = s$ are omitted. The right panel displays the probability of withdrawing cash as a function of m, i.e., the current level of cash balances. Two nonparametric fits with 95% confidence intervals are overlaid to each plot.
Data from ECB payment diaries: SUCH (2016) and SPACE (2019, 2021-22 and 2023-24).

B Theoretical appendix

B.1 Proof of Lemma 1

If $p(m,s)=0$, it means that $v(m-s) \leq v(m)+\kappa$. But then $v(m-s') \leq v(m-s) \leq v(m)+\kappa$ too if v is weakly decreasing. The second result follows from the same logic. ■

B.2 Proof of Lemma 2

Consider payments of size s such that $m-s \leq \underline{m}$. Agents are indifferent between using cash and cards if $m=\widetilde{m}$, where $\widetilde{m}$ solves $v(\widetilde{m})=v^*+b-\kappa$ and it is independent of s. As $v(m)$ is decreasing, $p(m,s)=1$ for $m>\widetilde{m}$ and $p(m,s)=0$ otherwise. A solution to $v(\widetilde{m})=v^*+b-\kappa$ exists if and only if $0<\kappa<b$, as $v(m) \in [v^*, v^*+b]$. Since i) v is weakly decreasing and continuous, ii) $v(\underline{m})=v^*+b$, and iii) $v(m^*)=v^*$, by the intermediate value theorem a solution $\tilde{m} \in (\underline{m}, m^*)$ exists, as desired. ■

B.3 Proof of Proposition 1

We now prove each point of Proposition 1.

1. Recall that the agent uses cards whenever $v(m-s) \geq v(m)+\kappa$. When $\kappa \leq 0$, this is always the case as v is weakly decreasing. This proves that for $\kappa \leq 0$, $p(m,s)=1$ for all (m,s), as desired. ■

2. (a) From Lemma 2, we know that when $m \in [\underline{m}, \widetilde{m}]$, $p(m,s)=0$ whenever $m-\underline{m} \leq s \leq m$. By Lemma 1, then $p(m,s)=0$ also for any $0 \leq s < m-\underline{m}$.

   (b) From Lemma 2 we know that for $m-s \leq \underline{m}$, we have $p(m,s)=1$ whenever $m \in [\widetilde{m}, m^*]$. By Lemma 1, this implies that there exists $\underline{s}(m) \leq m-\underline{m}$ such that $p(m,s)=1$ for all $s \geq \underline{s}(m)$, as desired. In particular, we have that $\underline{s}(m) < m-\underline{m}$ whenever

$$v(m-s) > v(m)+\kappa,$$

for some $m > \widetilde{m}$ and $s < m - \underline{m}$. Then, for any $m > \widetilde{m}$, $\underline{s}(m)$ is the solution to

$$v(m - \underline{s}(m)) = v(m) + \kappa,$$

which can be rewritten as

$$\underline{s}(m) = m - v^{-1}\left(v(m) + \kappa\right),$$

where $v^{-1}\left(v(m) + \kappa\right)$ is well-defined (it is a singleton) as v is strictly decreasing (hence invertible) on $[\underline{m}, m^*]$. ■

3. First, let's prove that when $\kappa > b$, $p(m, s) = 0$ for all m and for all $m - \underline{m} \leq s \leq m$, i.e., for all s such that $m - s \leq \underline{m}$. If $\kappa > b$, $v(m) > v^* + b - \kappa > v^*$ for any m, hence $p(m, s) = 0$ for all m and all $m - \underline{m} \leq s \leq m$. By Lemma 1, it has to be that $p(m, s) = 0$ even for $0 \leq s < m - \underline{m}$. Therefore, $p(m, s) = 0$ for all m and for any $s \leq m$, as desired. ■.

B.4 Additional results

We state and prove two additional results for the case $0 < \kappa < b$ that are not reported in the main text.

1. $\lim_{m \to \widetilde{m}_+} \underline{s}(m) = \widetilde{m} - \underline{m}$.

   Proof. $\lim_{m \to \widetilde{m}_+} \underline{s}(m) = \widetilde{m} - \lim_{m \to \widetilde{m}_+} v^{-1}(v(m) + \kappa) = \widetilde{m} - v^{-1}(v^* + b) = \widetilde{m} - \underline{m}$. ■

2. $\lim_{m \to m^*} \underline{s}'(m) = 1$

   Proof. If we differentiate Equation (7) of the main text we obtain

$$\underline{s}'(m) = 1 - (v^{-1})'\left(v(m) + \kappa\right) v'(m).$$

   Using the inverse function theorem, this yields

$$\underline{s}'(m) = 1 - \frac{v'(m)}{v'\left(v^{-1}(v(m) + \kappa)\right)}.$$

Let $\hat{m}(m)$ be the solution to $v(\hat{m}(m)) = v(m) + \kappa$. This leaves us with

$$\underline{s}'(m) = 1 - \frac{v'(m)}{v'\left(\hat{m}(m)\right)}.$$

If v is strictly convex for $m > \tilde{m}$, v' is decreasing in absolute value. Given that $\hat{m}(m) < m$, we have that $\underline{s}'(m) > 0$. Since v is strictly decreasing, $\underline{s}'(m) < 1$. Moreover, since $\lim_{m \to m^*} v'(m) = 0$, we have that $\lim_{m \to m^*} \underline{s}'(m) = 1$, as desired. ■

B.5 Derivation of Equation (8) of the main text

We show how to derive Equation (8) of the main text, the functional equation whose solution is the stationary distribution of cash holdings $h(m)$. We have that

$$\begin{aligned} h(m, t+\Delta) = (1-\lambda\Delta)h(m,t) + & \\ & + \lambda\Delta h(m,t)\left(1 - F(m)\right) + \\ & + \lambda\Delta h(m,t) \int_0^m f(s)\phi p(m,s) ds + \\ & + \lambda\Delta \int_m^{m^*} h(m',t) f(m'-m) \big(1 - \phi p(m', m'-m)\big)\, dm' \end{aligned}$$

Removing time indices and rearranging, we obtain

$$h(m,t)\lambda\Delta \left(F(m) - \int_0^m f(s)\phi p(m,s) ds \right) = \lambda\Delta \int_m^{m^*} h(m',t) f(m'-m) \big(1 - \phi p(m', m'-m)\big)\, dm'$$

which yields the desired result.

B.6 Derivation of Equation (9) of the main text

We show how to derive Equation (9) of the main text, the functional equation whose solution is the function $\mathcal{T}(m)$ which yields the average time to the next withdrawal as a function of current cash holdings m. We start from a discrete-time version of the equation and then take its continuous time limit. We have

$$\begin{aligned}\mathcal{T}(m) = {} & (1-\lambda\Delta)\left(\Delta+\mathcal{T}(m)\right)+ \\ & +\lambda\Delta\left(1-F(m)\right)\left(\Delta+\mathcal{T}(m)\right)+ \\ & +\lambda\Delta\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)\left[\Delta+\mathcal{T}(m-s)\right]ds+ \\ & +\lambda\Delta\int_{m-\underline{m}}^{m} f(s)\left(1-\phi p(m,s)\right)ds\cdot 0+ \\ & +\lambda\Delta\int_0^{m} f(s)\phi p(m,s)\left[\Delta+\mathcal{T}(m)\right]ds.\end{aligned}$$

Rearranging, we obtain

$$\begin{aligned}\mathcal{T}(m)\lambda\Delta\left(F(m)-\int_0^m f(s)\phi p(m,s)ds\right) = {} & \Delta-\lambda\Delta^2+ \\ & +\lambda\Delta^2\left(1-F(m)\right)+ \\ & +\lambda\Delta^2\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)ds+ \\ & +\lambda\Delta\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)\mathcal{T}(m-s)ds+ \\ & +\lambda\Delta^2\int_0^{m} f(s)\phi p(m,s)ds.\end{aligned}$$

Dividing everything by Δ we get

$$\begin{aligned}\mathcal{T}(m)\lambda\left(F(m)-\int_0^m f(s)\phi p(m,s)ds\right) = {} & 1-\lambda\Delta+ \\ & +\lambda\Delta\left(1-F(m)\right)+ \\ & +\lambda\Delta\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)ds+ \\ & +\lambda\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)\mathcal{T}(m-s)ds+ \\ & +\lambda\Delta\int_0^{m} f(s)\phi p(m,s)\left[\Delta+\mathcal{T}(m)\right]ds,\end{aligned}$$

and taking limits for $\Delta\to 0$ we finally obtain

$$\mathcal{T}(m)=\frac{1+\lambda\int_0^{m-\underline{m}} f(s)\left(1-\phi p(m,s)\right)\mathcal{T}(m-s)ds}{\lambda\left[F(m)-\int_0^m f(s)\phi p(m,s)ds\right]},$$

or, in terms of implied cash remaining $m' = m - s$,

$$\mathcal{T}(m) = \frac{1 + \lambda \int_{\underline{m}}^{m} f(m - m') \left(1 - \phi p(m, m - m')\right) \mathcal{T}(m') dm'}{\lambda \left[F(m) - \int_0^m f(m - m') \phi p(m, m') dm'\right]}.$$

B.7 Model-implied moments: additional details

Here, we provide additional details on the computation of model-implied moments, complementing Section 3.2 of the main text.

Computation of $\underline{M}$ and W. We now illustrate how to compute the average cash on hand when a withdrawal takes place, denoted by $\underline{M}$, as well as the average size of withdrawals W. To do that, we need to compute the stationary distribution of cash balances the moment *before* a payment that triggers a withdrawal takes place. Such a distribution is denoted by $h_w(m)$ and given by

$$h_w(m) = \frac{h(m) \left(\int_{m-\underline{m}}^{m} f(s) \left(1 - \phi p(m, s)\right) ds\right)}{\int_{\underline{m}}^{m^*} h(m) \left(\int_{m-\underline{m}}^{m} f(s) \left(1 - \phi p(m, s)\right) ds\right) dm + h(m^*) \left(\int_{m^*-\underline{m}}^{m^*} f(s) \left(1 - \phi p(m^*, s)\right) ds\right)},$$

where the numerator gives the flows into withdrawing coming from cash holdings m and the denominator represents aggregate flows into withdrawing. The boundary condition $\int_{\underline{m}}^{m^*} h_w(m) dm + h_w(m^*) = 1$ helps us pinning down the mass point $h_w(m^*)$. We can then use this probability distribution to compute $\underline{M}$. An extra step is involved: for any m, we should compute the expected value of s given that a withdrawal took place after a payment before which the individual had m on hand, and subtract it from m to obtain the amount of cash holdings $m - s$ right before the withdrawal took place (i.e., after the payment was settled using cash). We obtain

$$\underline{M} = \int_{\underline{m}}^{m^*} h_w(m) \left[\frac{\int_{m-\underline{m}}^{m} f(s)(m - s) ds}{\int_{m-\underline{m}}^{m} f(s) ds}\right] dm + h_w(m^*) \left[\frac{\int_{m^*-\underline{m}}^{m^*} f(s)(m^* - s) ds}{\int_{m^*-\underline{m}}^{m^*} f(s) ds}\right], \qquad (2)$$

which implies an average withdrawal size $W = m^* - \underline{M}$.

Computation of γ_n and $\widetilde{\gamma}_n$. The statistics γ_n and $\widetilde{\gamma}_n$, which measure the share of purchases settled with cards (both overall and when both payment methods were available) can be computed through a slight modification of Equations (10) and (11) of the main text. The only difference is that now we don't consider the size of each purchase when computing the share. The card share of purchases γ is given by

$$\gamma_n = \frac{\lambda\phi\left(\int_{\underline{m}}^{m^*} h(m)\gamma_n(m)dm + h(m^*)\gamma_n(m^*)\right)}{e}, \tag{3}$$

where $\gamma_n(m) = \int_0^m f(s)p(m,s)ds + (1 - F(m))$ is the share of purchases paid with cards when having m units of cash on hand. We also want to capture how often cards are used conditional on having both options available, i.e., for *unforced* purchases. The card share of unforced purchases $\widetilde{\gamma}_n$ is computed as

$$\widetilde{\gamma}_n = \frac{\lambda\phi\left(\int_{\underline{m}}^{m^*} h(m)\left(\int_0^m f(s)p(m,s)ds\right)dm + h(m^*)\left(\int_0^{m^*} f(s)p(m^*,s)ds\right)\right)}{\lambda\phi\left(\int_{\underline{m}}^{m^*} h(m)\left(\int_0^m f(s)ds\right)dm + h(m^*)\left(\int_0^{m^*} f(s)ds\right)\right)}. \tag{4}$$

B.8 Card usage probabilities as a function of m, s and $m' = m - s$

We can compute the probability of cards being used as a function of some important determinants of payment choices, namely m, s and $m' = m - s$. Computing such objects requires knowing i) the invariant distribution of cash holdings $h(m)$, ii) the size distribution of payments $f(s)$, and iii) payment choice probabilities $p(m,s)$. For each of these, we can compute both the *overall* probability of card usage and the probability *conditional* on having both options available (for *unforced* purchases). We start from $\Pr_{\text{ccard}}(s)$, the probability of a card payment when agents face a purchase of size s, which is given by

$$\Pr_{\text{card}}(s) = \phi\left(H(s) + \int_s^{m^*} h(m)p(m,s)dm + h(m^*)p(m^*,s)\right), \tag{5}$$

where H is the cdf associated with the invariant distribution of cash holdings h. Cards are used to settle a purchase of size s whenever i) they are accepted, and ii) either cash holdings are not enough to cover for the transaction, or they are sufficient but cards are chosen nonetheless. The probability of card usage to settle a purchase of size s for an unforced purchase is instead given by

$$\widetilde{\Pr}_{\text{card}}(s) = \frac{\phi\left(\int_s^{m^*} h(m)p(m,s)dm + h(m^*)p(m^*,s)\right)}{\phi\left(1 - H(s)\right)}. \tag{6}$$

Similarly, the unconditional probability $\Pr_{\text{card}}(m)$ of using cards when having m cash balances on hand is given by

$$\Pr_{\text{card}}(m) = \phi\left(\int_0^m f(s)p(m,s)ds + (1 - F(m))\right), \tag{7}$$

while its counterpart for unforced purchases is given by

$$\widetilde{\Pr}_{\text{card}}(m) = \frac{\phi \int_0^m f(s)p(m,s)ds}{\phi F(m)}. \tag{8}$$

Finally, we can write $\Pr_{\text{card}}(m')$, the probability of card usage conditional on implied cash remaining in case of a cash payment being equal to $m' = m - s > 0$. Notice that since we focus on $m' > 0$, we only compute this statistic for unforced purchases, i.e.,

$$\widetilde{\Pr}_{\text{card}}(m') = \frac{\phi\left(\int_{m'}^{m^*} h(m)f(m-m')p(m,m-m')dm + h(m^*)f(m^*-m')p(m^*,m^*-m')\right)}{\phi\left(\int_{m'}^{m^*} h(m)f(m-m')dm + h(m^*)f(m^*-m')\right)}. \tag{9}$$

C Calibration details

C.1 Withdrawal frequency

As shown in Table 1 of the main text, the probability that respondents report to have withdrawn cash during the diary day rises strongly over the four survey waves. As a result, the estimated average number of withdrawals per year increases from about 40 in 2015-16 to around 95 in 2023-24 (see Table 2). This large increase could result from changes in the questionnaire methodology over time. In SUCH and SPACE 2019, consumers were asked how much cash they added to their wallets during the diary day; we use those responses to generate a dummy for whether a withdrawal took place or not. Since SPACE 2021-22, respondents are explicitly asked " *Did you do any of the following on [DIARY DAY]? (1) Cash*

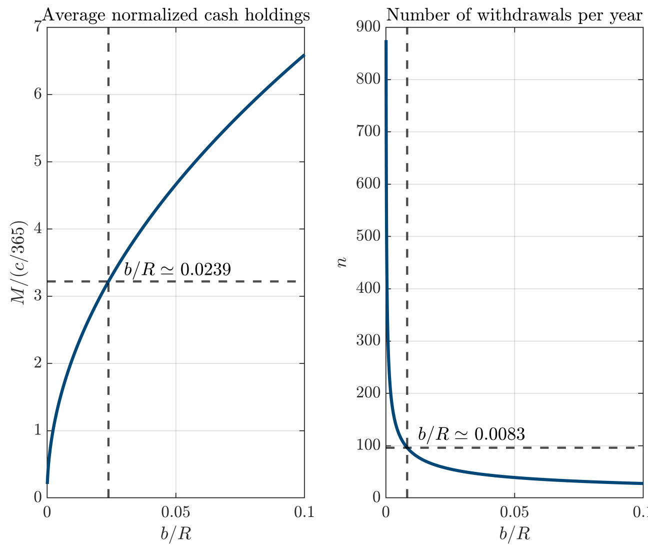
TABLE 2: All statistics, by wave.

	(1) 2015-16	(2) 2019	(3) 2021-22	(4) 2023-24
Expenditure stream				
Number of payments per day $\hat{\lambda}$	1.83	1.69	1.93	1.90
Daily expenditure $e/365$ (EUR)	34.03	46.28	63.89	61.23
Daily cash expenditure $c/365$ (EUR)	18.31	21.96	27.15	25.48
Cash holdings				
Cash holdings M (EUR)	59.85	82.55	84.98	81.93
Normalized cash holdings $M/(e/365)$	1.76	1.78	1.33	1.34
Normalized cash holdings $M/(e/365)$ (median)	0.95	0.86	0.78	0.95
Normalized cash holdings $M/(c/365)$	3.27	3.77	3.17	3.22
Withdrawals				
Number of withdrawals per year n	39.75	46.26	80.81	96.63
Implied number of withdrawals per year n	95.92	88.90	91.08	96.40
Withdrawal size W (EUR)	69.66	90.15	108.81	96.47
Normalized withdrawal size W/M	1.16	1.09	1.28	1.18
Payment choice sets				
Unforced, % share of transactions	0.63	0.66	0.66	0.73
Forced cash, % share of transactions	0.28	0.20	0.15	0.11
Forced card, % share of transactions	0.09	0.14	0.19	0.16
Unforced, % share of expenditure	0.54	0.51	0.52	0.62
Forced cash, % share of expenditure	0.17	0.14	0.11	0.08
Forced card, % share of expenditure	0.29	0.35	0.36	0.30
Payment choices				
Paid card, % share of transactions γ_n	0.25	0.32	0.44	0.49
Paid card (if card possible), % share of transactions $\dot{\gamma}_n$	0.35	0.40	0.51	0.55
Paid card (if unforced), % share of transactions $\widetilde{\gamma}_n$	0.26	0.27	0.37	0.45
Paid card, % share of expenditure γ	0.46	0.53	0.58	0.58
Paid card (if card possible), % share of expenditure $\dot{\gamma}$	0.56	0.61	0.65	0.64
Paid card (if unforced), % share of expenditure $\widetilde{\gamma}$	0.32	0.35	0.41	0.46

withdrawal (e.g. ATM machines, bank counter, supermarket or shop)". To check the accuracy of the withdrawal frequency measure and ensure comparability across survey waves, we adopt the following procedure. We rely on the accounting identity

$$nW = (1 - \gamma)e, \tag{10}$$

Figure C.1: The simple BT model and SPACE data for 2023-24.



Note: The figure shows, for a wide range of values of the ratio b/R, the values of model-implied moments M_c and n in the simple BT framework. In each plot, we display the value of b/R that enables the BT model to match the empirical counterparts $\widehat{M}_c$ and $\widehat{n}$ (calculated on 2023-24 SPACE data).

that states that, on aggregate, the average number of withdrawals per year multiplied by the mean withdrawal size should be equal to the yearly cash expenditure. We assume that $\{W, \gamma, e\}$ are measured accurately and compute

$$n_{implied} = \frac{(1-\widehat{\gamma})\widehat{e}}{\widehat{W}},$$

which we report in Table 2 as well. For the last available wave, the number of withdrawals implied by the accounting identity is remarkably close to the actual one. For SPACE 2021-22, it is slightly higher, while it is much higher for the first two waves. Over time, the implied number of withdrawals is much more comparable. Therefore, we use the implied number of withdrawals in our calibrations, for all waves and all demographic subgroups.

C.2 A benchmark: the standard BT model

We now discuss the calibration of a simple BT model to 2023-24 data, and compare the estimated total cost of managing consumption transactions that one would derive from calibrating a simple BT model with our estimates based on the augmented model.

TABLE 3: Withdrawal cost b and total cost $\mathcal{C}^{BT}$, for different R.

	Calibration target			
	$\widehat{M}_c$		$\widehat{n}$	
Opportunity cost R	b (EUR)	$\mathcal{C}^{BT}$ (EUR)	b (EUR)	$\mathcal{C}^{BT}$ (EUR)
1%	0.015	1.677	0.005	0.990
2%	0.030	3.354	0.010	1.980
5%	0.074	8.385	0.026	4.950
10%	0.148	16.770	0.052	9.901

Calibrating the BT model. Consider the canonical BT model with parameters (b, R, c). Let $c = (1-\gamma)e$ be annual cash expenditure, and $e = 365$ be the annual expenditure. Assume that γ is given, and that agents finance an infinitesimal consumption stream c as in the BT model. Average cash holdings over daily cash expenditure and the yearly number of withdrawals are given by

$$M_c = \frac{M}{c/365} = 365\frac{\sqrt{bc/2R}}{c} = 365\sqrt{\frac{b}{2R(1-\gamma)365}} = \sqrt{\frac{365b}{2R(1-\gamma)}}, \tag{11}$$

$$n = \sqrt{\frac{Rc}{2b}} = \sqrt{\frac{R(1-\gamma)365}{2b}}, \tag{12}$$

with their ratio being given by

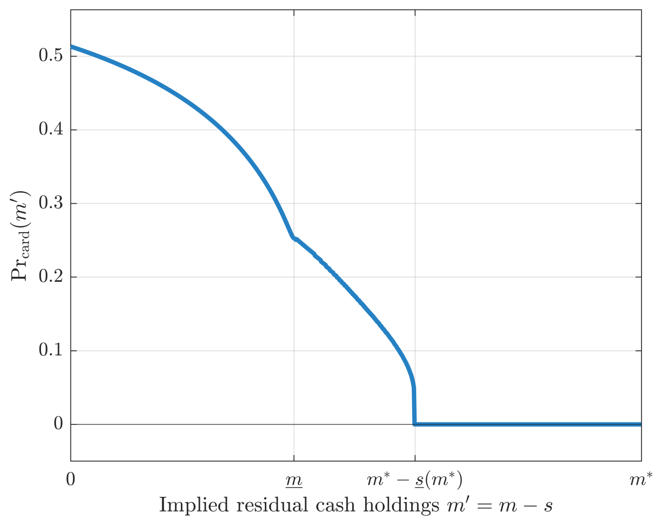
$$\frac{M_c}{n} = \frac{b}{R(1-\gamma)}$$

In our data for 2023-24 (the most recent wave) we have $\widehat{M}_c = 3.22$, $\widehat{\gamma} = 0.58$ and $\widehat{n} = 96.4$. Assume we target $\widehat{M}_c$; from Equation (11), this implies $\frac{b}{R} \simeq 0.0234$. Assume that instead we target $\widehat{n}$; from Equation (12) this yields $\frac{b}{R} \simeq 0.0083$. The BT model cannot fit both moments at the same time while simultaneously matching $\widehat{\gamma}$. Figure C.1 shows this graphically: the observed $\widehat{M}_c$ is consistent with a ratio b/R around 3 times higher than what the average number of withdrawals per year $\widehat{n}$ implies.

Total cost in the BT model. As an additional exercise, we compute the total cost implied by the BT model when targeting $\widehat{M}_c$ or $\widehat{n}$ respectively. Total costs of managing consumption transactions in the BT model are given by $\mathcal{C}^{BT} = RM + bn$. In Table 3, we display, for several values of R (including our benchmark of 10% used in the calibration), the value of b needed to match either cash holdings or the frequency of withdrawals, and the implied values of $\mathcal{C}^{BT}$. When $R = 10\%$, as in our calibration in the main text, and we target average normalized cash holdings, we find a value of total costs in line with our estimates from the augmented model.

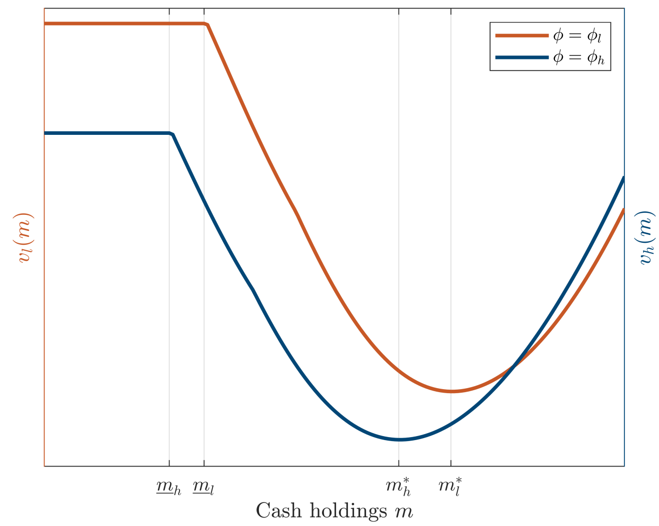
D Model and calibration: additional figures and tables

FIGURE D.1: Probability of card usage as a function of implied residual cash balances.



Note: The graph shows the model-implied predicted probability $\widetilde{\mathrm{Pr}}_{\text{card}}(m')$ of card usage as a function of implied remaining cash holdings if the purchase is settled in cash $m' = m - s$. $m^* - \underline{s}(m^*)$ is the smallest level of implied remaining cash holdings that triggers some card usage. Parameters are those obtained from the calibration of the model for 2021-22 discussed in Section 4 of the main text.

Figure D.2: The effect of card acceptance in the model.



Note: The figure displays the value function $v(m)$ for two values of the card acceptance rate ϕ, with ϕ_l denoting lower card acceptance and ϕ_h denoting higher card acceptance. To produce the plots, we set $\phi_l = 0.85$ and $\phi_h = 0.89$, and we keep all the other parameters at their levels obtained from the calibration of the model for 2021-22 discussed in Section 4 of the main text. We plot the two value functions on separate y-axes, so their levels are not comparable.

Figure D.3: Total cost, all waves.

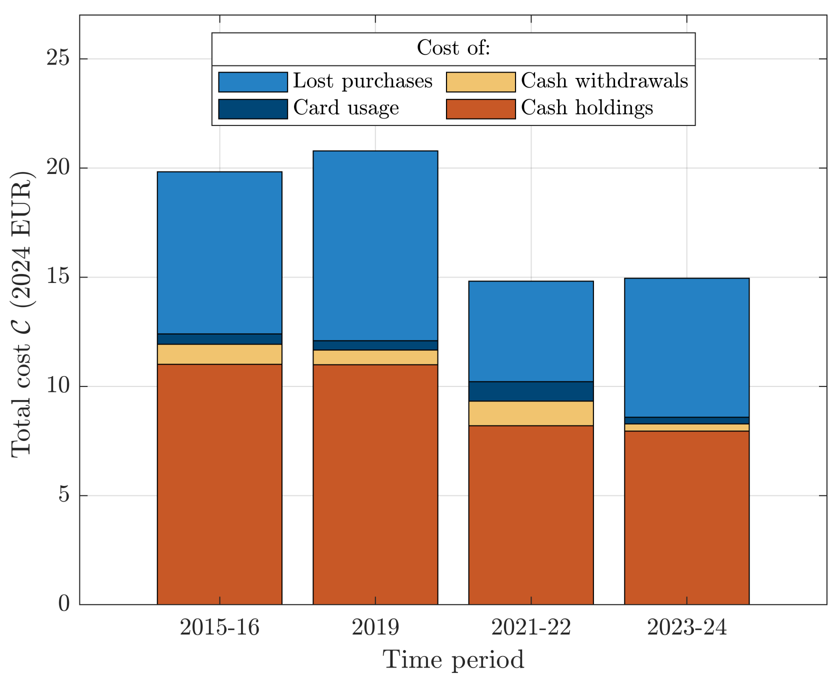


Table 4: Parameter estimates, all waves.

	Time period			
	2015-16	2019	2021-22	2023-24
Externally calibrated parameters				
Purchase size distr. F, location μ_s	-1.840	-1.823	-1.568	-1.955
Purchase size distr. F, scale σ_s^2	2.473	2.602	1.817	2.630
Card acceptance rate ϕ	0.722	0.802	0.848	0.894
Internally calibrated parameters (minimum distance)				
Withdrawal cost b (EUR)	0.005	0.006	0.013	0.003
Card usage cost κ (EUR)	0.003	0.004	0.007	0.002
Lost purchase cost u (EUR)	0.288	0.627	0.527	0.976
Purchase opport. per day $\lambda/365$	1.876	1.722	1.982	1.923

Figure D.4: Total cost, 2023-24, subgroups.