Payments and Cash Management in the Euro Area
Data, Theory and Quantitative Analysis

Elia Moracci*

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Abstract

Exploiting unique, previously unexplored transaction-level microdata from two ECB surveys on payment and cash management attitudes of consumers in the Euro Area, I provide new facts on the interaction between payment choices, cash management decisions and merchant acceptance of payment instruments. I build a simple analytical model with rationalizes a key fact: as uncertainty over the sizes of future purchases and imperfect cashless acceptance generate a precautionary motive for holding cash, it can be optimal for individuals to pay using cashless methods even when cash on hand would be enough to carry out the transaction, in order to keep cash holdings close to their optimal level. The model generalizes existing results and rationalizes features of behavior that previous theories could not account for. I then develop a quantitative model with heterogeneous households that embeds features such as imperfect cash acceptance and information on the size of incoming purchases, and I estimate its parameters at the country level using 2019 data. Preliminary results suggest that differences in supply-side constraints explain only a fraction of cross-country variation in payment and cash management behavior, with other factors such as heterogeneity in buyers' tastes for cashless payments and in the opportunity cost of holding cash playing a sizeable role.

Keywords: *payment choices, cash management, cashless payments, monetary economics.*

JEL Codes: *E41, E42, D14.*

*Research Student in Economics, European University Institute. Mail: elia.moracci@eui.eu.
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1 Introduction and overview

Why is cash still around? Why do the adoption, usage, and acceptance of cashless methods differ so widely across and within countries? Will cash be resilient to innovations in payment technologies brought up by rapid technological change? These are relevant questions in monetary economics that, as of today, remain partially unanswered, despite their substantial policy relevance at present times. As intensive cash usage is associated with crime and tax evasion (Rogoff (2017)), over the last years the governments of several countries have imposed limits to cash payments, such as caps to large cash transactions, or have put forth measures to incentivize card adoption and usage (a notable example is the 2020 Italian *cashback* policy). Recent inflationary pressures are also likely to revive the discussion on the welfare costs of inflation related to the transactions demand for cash (Alvarez, Lippi, and Robatto (2019)), which could be affected by the availability and usage of alternative payment technologies. Finally, as changes brought up by the pandemic seemingly accelerated the transition to a world with less cash, more than 75 central banks (Abramova et al. (2022)) are now examining the possibility to upgrade their payment systems by introducing central bank digital currencies (CBDC). Whether implementing the Fedcoin or the digital euro are good ideas or not also depends on the willingness of people to use them as payment methods. To be well equipped to tackle such complicated issues, however, one needs to start by understanding the payment behavior of individuals and its relationship with cash management - namely, why people use cash or cashless methods to carry out their purchases and how they decide on how much cash to hold. The welfare effects of cash bans, as well as the consequences of incentives aimed at fostering cashless usage, can only be evaluated within a theoretical framework where payment and cash management decisions are based on explicit household optimization. The goal of this paper is to combine data, theory, and quantitative analysis to present and estimate a model designed to capture the relevant tradeoffs faced by households when deciding on how to pay for goods and services and on how much cash to hold.

This work leverages on data from two ECB surveys on payment and cash management behavior in the Euro Area: the Survey on the Use of Cash by Households (2016, SUCH from now on), and the Study on the Payment Attitudes of Consumers in the Euro Area (2019, SPACE from now on). My analysis starts with an empirical investigation of cash management and payment behavior in the Euro Area. Drawing upon detailed payment diaries, which enable me to observe consumers' *payment choice sets* (the set of payment instruments available that consumers can choose to settle each purchase), I confirm the two main predictions of the empirical literature on payment choices: the probability of using cash to settle a transaction is decreasing in the size of the purchase and increasing in the amount of cash held. I also present a novel stylized fact: individuals are more and more likely to employ cashless payments when the purchase size is very close to the amount of cash held, to avoid running out of cash. This effect is more intense when imperfect acceptance of cashless instruments induces a precautionary motive for holding cash - individuals want to avoid situations in which they have low cash holdings if they frequently run into shops that do not accept cards.

I then show that some relevant features of observed behavior are inconsistent with two benchmark models in the payment choice literature, those by Whitesell (1989) and Alvarez and Lippi (2017). The empirical results outlined above offer a possible explanation for this gap between data and theory, as in these models payment choices either depend on purchase sizes alone (in Whitesell (1989)) or cash holdings alone (in Alvarez and Lippi (2017)). Building on this intuition, I outline a novel, stylized two-period model of payment choices that combines features of both frameworks in a unified fashion. Despite its simplicity, the model can rationalize behavior that previous frameworks could not account for, while, at the same time, matching established facts on payment choices. A key result is that individuals will depart from the policies of Alvarez and Lippi (2017), using cards even if they have enough cash, when the cost[1] of using cashless payments is low relative to that of withdrawing: people use their cashless payment instruments as cash management devices, to avoid visiting ATMs too often. Combining transaction-level data with information on the cost of withdrawals provided in the survey questionnaire, I show that this prediction is supported by empirical evidence.

As the stylized framework is too simplified to enable structural estimation, I then build an augmented, quantitative version of the model, where I include heterogeneity in the taste for cashless payments and the possibility that agents, to some extent, have information on the size of incoming payments. The quantitative model also features a realistic portray of supply-side constraints to payment choices, in the form of different regimes of payment method acceptance by merchants whose probabilities I calibrate from the data. After describing cross-country heterogeneity in payment and cash management behavior in the Euro Area, I estimate the model for each country in 2019 exploiting the informational content of SUCH data. The structural estimation relies on the method of simulated moments, targeting relevant cash management and payment choice statistics. The estimated models reveal that cross-country differences are not entirely attributable to supply-side constraints such as limited cashless acceptance by merchants, but that regional variation in demand-side factors (mostly in the taste for cashless usage and in the cost of holding cash) also plays a sizeable role.

[1]The cost of cashless payments embeds both monetary and non-monetary factors. The former type of cost includes fees that are paid when using the card, which are however getting less and less relevant. The latter, instead, captures other kinds of costs perceived by consumers when using cashless methods: privacy costs (as the transaction can be perceived as not being anonymous anymore) and time costs (as the literature has shown that cash payments are settled more quickly, see Klee (2008)). Of course, this cost can be *negative* for some people or in some situations, if they prefer to use the card to settle the transaction. Estimating the distribution of such costs/benefits of using cards is part of the goal of this paper.

1.1 Related literature and contribution

The bulk of the literature on payment choices and cash management consists of empirical work. Most studies in this area of research make use of micro-level evidence such as payment diaries or stores' transaction data in order to study the determinants of consumers' payment method choices. The set of factors reportedly associated with more or less intensive cashless usage is large, ranging from demographics such as age and education to economic determinants such as income. Some determinants of payment method decisions are particularly relevant for the present paper.

A first important association is the one between payment method decisions and the size of the purchase. Exploiting grocery store data, Klee (2008) finds that cash is mainly used for small-sized purchases, while cashless payments are prevalent when the value of the sale increases. Similar results are obtained by Wang and Wolman (2016) leveraging on scanner data from two billion retail transactions, and by many other studies. A second relevant determinant of cash/cashless choices is the amount of cash on hand at the moment when the transaction is settled. All papers that analyzed the effect of cash holdings on payment choices (Arango, Huynh, Fung, et al. (2012), Bouhdaoui and Bounie (2012), Huynh, Schmidt-Dengler, and Stix (2014), Bagnall et al. (2016)) consistently found that the likelihood of cash usage increases with the level of cash holdings. A third potential determinant of payment choices by individuals are also supply-side factors such as limited acceptance of means of payments. This is confirmed by Arango, Huynh, and Sabetti (2015), that exploits survey data to show the relevance of the probability of merchant acceptance in shaping means of payments decisions by consumers. Moreover, a number of studies (see for example Bagnall et al. (2016)) have observed an interplay between payment choices and cash management decisions, finding a positive association between cash usage at POS, the frequency and size of withdrawals, and average cash holdings.

I contribute to this empirical literature in several ways. Using a rich payment diary I show stylized facts on payment choices in the Euro Area context for the period 2016-2019. In addition to presenting evidence that supports previous findings, I show a novel result: agents decide whether to pay with cash or cashless taking into account the effect of their choice on future cash holdings and on the related cash management costs. This finding supports the view that payment and cash management decisions must be studied jointly. Finally, I document that expected levels of payment methods acceptance affect both cash management patterns and payment method decisions.

Despite most of the work on payment choices is empirical, there are several papers that tackled the problem from a theoretical perspective. However, only a handful of studies tried to combine the study of payment decisions with that of cash management by households, embedding a means of payments choice in the standard model by Baumol (1952) and Tobin (1956). Whitesell (1989) augments a static Baumol-Tobin model with a non-degenerate distribution of transaction sizes and a choice among cash and cashless payments. In this model, it is optimal to pay by cash whenever the size of the transaction is smaller than a given threshold, and to pay using cards otherwise (*transaction size threshold* policies). In a more recent paper, Alvarez and Lippi (2017) abstract from transaction size heterogeneity and present a dynamic model where payment choice rules only depend on cash holdings, showing that for small payment sizes cash usage is optimal whenever agents have enough (*cash burns* policies). Notice that the predictions of both these models are qualitatively consistent with the above-cited empirical findings on the relationship of payment choices with transaction sizes and cash holdings. In contemporaneous work, Briglevics and Schuh (2021) solve a model in which agents' decisions on how to pay depend both on the size of the transaction and on the amount of cash held, within a dynamic cash management framework, and they estimate it to US payment diary data.

The contribution of the present paper to this literature is threefold. First, I show that the models by Whitesell (1989) and Alvarez and Lippi (2017) don't capture two salient features of payment behavior, namely i) that payment choices depend both on the size of purchases *and* on the level of cash holdings, and ii) that oftentimes people find it optimal to use cashless methods even when they have enough cash on hand - especially if cashless acceptance is imperfect. Second, I present a novel, stylized model of cash management and payment choices that generates novel results, offering a theoretical explanation for how cashless usage can be optimal even when cash on hand is enough to complete transactions. Third, I estimate a quantitative extension of such model to match the observed cross-country heterogeneity in cash management and payment behavior in the Euro Area. Relative to the contemporaneous work by Briglevics and Schuh (2021), the main novelty is the ability to disentangle differences in behavior induced by heterogeneity in consumers' preferences from those produced by variation in merchant acceptance of payment methods.

1.2 Structure of the paper

In Section 2 I describe SUCH and SPACE data and I perform an empirical analysis of payment behavior in the Euro Area. I connect my findings with previous empirical results and with the predictions of the relevant theoretical literature, highlighting some facts which cannot be rationalized by existing models and documenting novel features of payment behavior. In Section 3 I present a simple, two-period model of payment choices and cash management. I discuss properties of the model's solution, evaluate if additional predictions of the theory are consistent with survey data, and connect my findings to the existing literature, showing that optimal policies in my model are a generalization of previous work. In Section 4 I start by highlighting the most relevant features that a structural model of cash management and payment choices must possess

Table 1: Summary statistics.

	Mean	Median	SD	P_1	P_{99}	N
Payment choices						
Payment size (€)	21.38	8.52	87.35	0.40	199.60	155,565
Paid cashless	0.26	0.00	0.44	0.00	1.00	155,565
Cashless accepted	0.74	1.00	0.44	0.00	1.00	152,360
Cashless possible	0.68	1.00	0.47	0.00	1.00	129,158
Cash accepted	0.97	1.00	0.16	0.00	1.00	65,119
Cash possible	0.89	1.00	0.31	0.00	1.00	178,472
Both methods possible	0.53	1.00	0.50	0.00	1.00	129,169
Paid cashless | Both poss.	0.32	0.00	0.47	0.00	1.00	69,013
Cash management choices						
Cash holdings (€)	68.47	35.77	152.86	0.00	500.00	178,472
Withdrawn	0.06	0.00	0.23	0.00	1.00	90,843
Withdrawal size (€)	82.48	40.00	153.58	1.80	550.00	4,982
Adjusted	0.08	0.00	0.27	0.00	1.00	90,843
Adjustment size (€)	75.03	35.00	145.01	1.00	540.00	6,502

Note: Adjustments are defined as any increase in cash holdings between a payment and another; they also include receiving money from friends, or as cash income. Withdrawals are a particular type of adjustment: in these cases, agents either withdrew money from an ATM or got it from a bank teller. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

in order to be brought to the data for estimation. Afterwards, I present the quantitative model, discussing its structure, timing, the relevant choices faced by households and the solution method. After describing the functional form assumptions and the numerical solution technique, I describe my estimation strategy. In Section 5, after a brief description of cross-country heterogeneity in payment choices and cash management within the Euro Area, I present estimation results for all countries in my sample. Then, I discuss the results and their implications. Finally, I describe potential improvements of the estimation strategy and ideas for future research that can build on this work. Section 6 concludes.

2 Empirical analysis

2.1 Data: SUCH and SPACE surveys

I start by providing an overview of the two data sources used in this paper. Throughout the analysis, I exploit microdata on payment choices and cash management behavior of individuals from 15 Euro Area countries, combining two datasets provided by the

ECB jointly with two publications: the first one, released in 2016, is the Study on the Use of Cash by Households (SUCH from now on); the second one, released in 2020, is the Study on the Payment Attitudes of Consumers in the Euro Area (SPACE from now on)[2]. Each study contains a payment diary and a survey questionnaire: in the diary, participants recorded information on all their payments and adjustments of cash balances in a given day; within the questionnaire, they were asked a number of questions on their preferences about payment methods, on the set of cashless instruments they had access to and on their cash management behavior.

The main variables are summarized in Table 1. A key characteristic of these data is that one can combine the information provided to track down the time path of cash holdings and to elicit *payment choice sets* of consumers (whether cash or cashless or both could be used to carry out purchases) for each transaction during the day of analysis. This feature enables me to distinguish between *voluntary payments* and *forced* ones. I define a payment as *voluntary* when the agent has both options available: she holds sufficient cash, she has access to cashless payment method and the current store accepts both cash and cashless payments. Payment method choices that do not satisfy one of these conditions are *forced*, as in these situations the payment choice set collapses to a singleton [3].

The ability of observe cash holdings at each point in time creates a unique setup to study payment choices. In most existing studies that analyzed payment behavior, payment choice sets are not appropriately taken into account because cash holdings at the time of each transaction are typically unobserved. Klee (2008) exploits grocery store data, thereby ruling out imperfect acceptance of cashless and cash payments: however, her strategy does not differentiate between voluntary cashless payments (in which the agent also had the opportunity to pay with cash) and forced ones (in which the agent did not have enough cash to carry out the purchase). A similar problem is encountered by Wakamori and Welte (2017): while they do observe perceived payment acceptance by agents, they don't know how much cash do they have at each point in time. In both papers, the authors can *limit* the choice sets of agents, but do not *observe it* in an exact way. In a similar but opposite fashion, in Briglevics and Schuh (2021) the authors have full information on the amount of cash holdings that agents have at each point in time, but they don't observe the payment method acceptance policy of the shops where each transaction took place. The data used in this paper makes choice sets exactly observable: this allows me to understand if a choice is driven by preferences or it is just the by-product of a trivial payment choice set.

[2] For further information about the methodology and results of these two studies, see respectively Esselink and Hernández (2017) and ECB (2020).

[3] Appendix A.1 contains details on the data cleaning procedure that enables me to derive the time path of cash holdings and therefore to elicit payment choice sets.

2.2 Payment choices and the data

As summarized in the literature review, empirical research on payment choices has put together a set of very robust stylized facts. Among these, two findings are the most consistent ones. First, the probability of using cashless methods is increasing in the size of the purchase. Second, individuals are more likely to pay using cashless methods when they have less cash on hand. Both effects are likely to be biased upwards when payment choice sets are not observed, for two reasons: first, the probability of cashless methods being accepted by merchants is increasing in the size of the transaction; second, when transactions are larger it is more likely to have insufficient cash to settle the purchase. My first goal is to exploit the fact that I fully observe the set of payment choices available for agents in each transaction, in order to see if these facts are still robust if one only takes into account transactions in which individuals had both payment options available[4]. Figure 1 reveals that this is indeed the case. It displays the share of transactions settled in cash for different values of cash holdings (which I call m) and purchase size (which I call s), in situations where both cash and cashless payments were feasible options for the buyer. First, the Figure shows that agents tend to use cashless methods more and more often as the size of the transaction s increases, a fact which is in line with findings by Klee (2008) and Wang and Wolman (2016). Second, agents are more likely when cash holdings m are larger, again consistently with existing work by Huynh, Schmidt-Dengler, and Stix (2014) and Bagnall et al. (2016), among others.

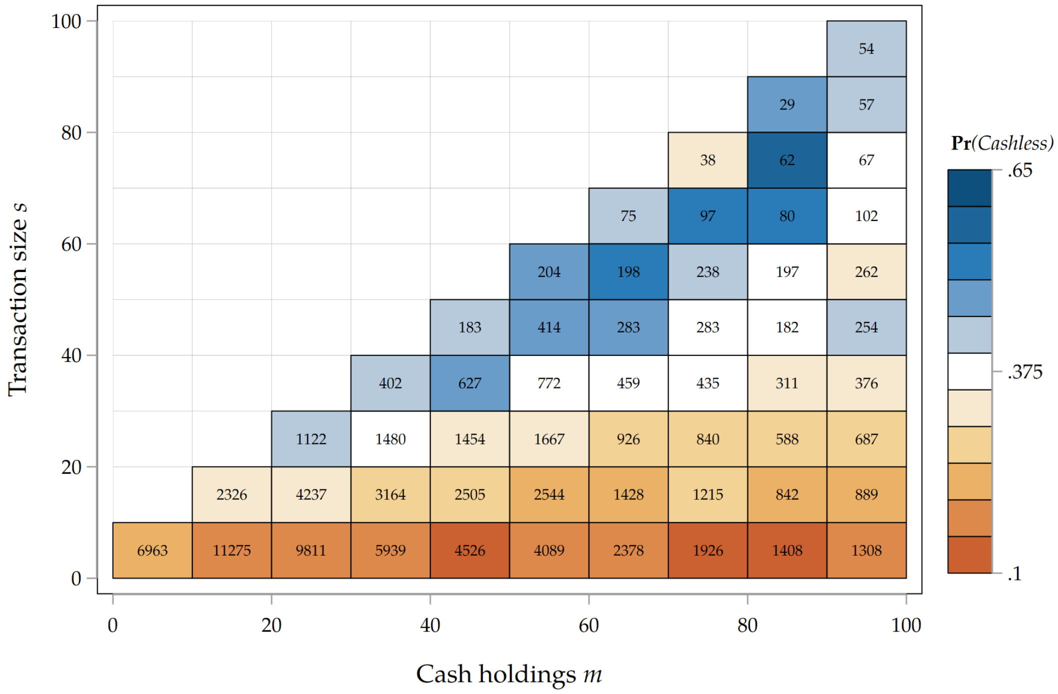
Fact 1. *The probability of cashless usage is increasing in the size of the purchase s and decreasing in the amount of cash on hand m.*

The above stylized fact is also consistent with the predictions of theoretical models of payment choice: as in Whitesell (1989), larger transactions are settled with cashless more often; as in Alvarez and Lippi (2017), larger amounts of cash holdings are associated with more intense cash usage.

Figure 1 also illustrates a second fact. When the transaction size s is very close to m (just below the 45° line in the graph) cashless is employed much more often. It seems that agents want to avoid using cash when this leads to an almost complete depletion of their money holdings, if they can avoid doing it by paying with their alternative payment method. This suggests that people take into account expected cash management costs when deciding on how to pay, if they have both options (cash and cashless) available. To see this, first notice that from a cash management perspective, the two payment methods are inherently different: when holding m units of cash, paying a transaction of size s using a cashless instrument leaves cash balances unchanged (fu-

[4] In order for both cash and cashless to be feasible payment options, three conditions have to be met: i) cash on hand is sufficient to carry out the purchase; ii) the buyer has access to a cashless payment method; iii) the merchant is willing to accept both cards and cash.

Figure 1: Share of cash payments for different m and s.

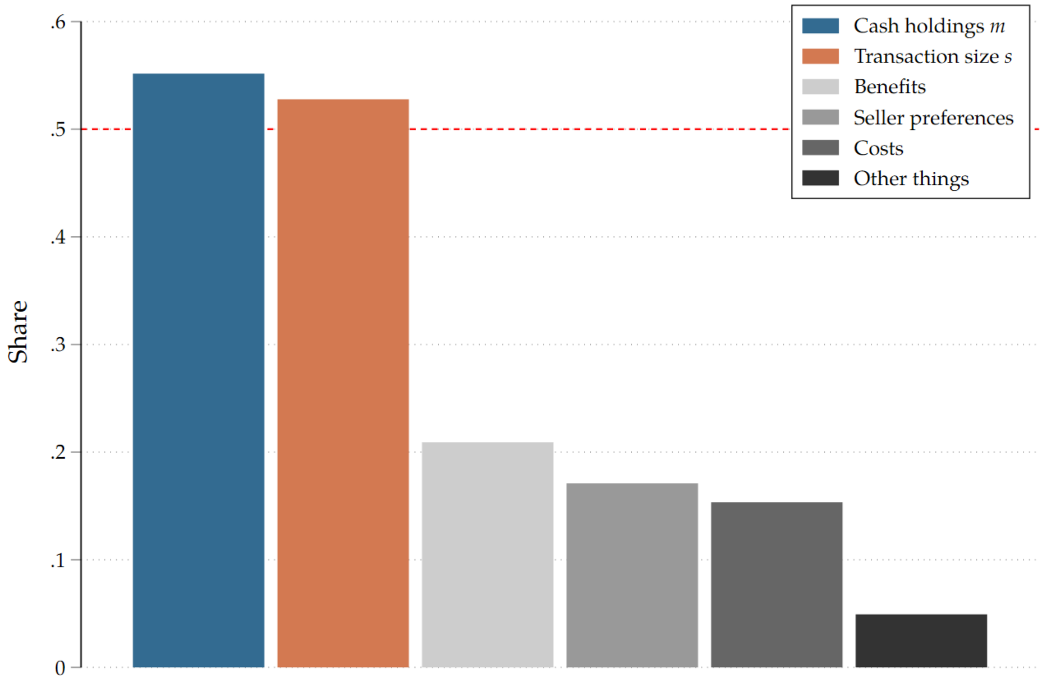


Note: This graph displays the shares of people paying with cash (when both payment options are possible) for bins defined in terms of cash holdings at payment (m) and transaction size faced (s). The share of people paying by cash is represented by the color of each cell, whereas the numbers displayed on cell denote the number of observations falling in that particular (m, s) bin. I focus on transactions where m and s are smaller or equal than 100 euros to avoid having cells with a very small number of observations. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

ture cash balances m' are equal to m), whereas using cash depletes them ($m' = m - s$). When facing an opportunity to pay with both methods, it is natural to think that agents will take three things into account: i) the cost/benefit of performing a cashless payment with respect to a cash one; ii) the amount of cash holdings left in case they pay using cash; iii) their current cash holdings, which they will keep if they decide to pay using their cards. Notice that choosing whether to pay using cash or cards has a direct impact on future cash management choices: cashless usage keeps money balances intact, postponing the need to withdraw cash. The SUCH survey questionnaire provides useful information on whether individuals really care about m and s when making a payment method decision. In Figure 2, I plot the shares of agents that say if a set of factors (among which m and s) affect their means of payments choice. We see that a large share of agents (more than 50%) takes into account these two factors when paying. We also see that compared to other factors, the size of the withdrawal and the size of the transaction are perceived as much more crucial for choosing on how to pay. This is suggestive evidence that people really take into account the effect of payment choices on future cash holdings, in line with the results of Figure 1.

Fact 2. *Cashless methods are often employed when the transaction size is big* relative *to cash*

Figure 2: Determinants of consumers' choice of payment instrument at the point of sale.



Note: This graph displays the shares of people 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.*

holdings, i.e., when $m' = m - s$ *is close to zero. Both* m *and* s *are relevant for payment decisions.*

As done for Fact 1, I now compare these findings with the predictions of Whitesell (1989) and Alvarez and Lippi (2017). None of the two models features decision rules that depend *both* on the size of the transaction faced and on the amount of cash holdings. In Whitesell (1989), choices depend on s, not on m; in Alvarez and Lippi (2017), the opposite holds. Both models assume away, or do not explicitly consider, the interaction between m and s that Fact 2 describes. This makes these theories unable to rationalize two relevant features of the data.

Regarding Whitesell (1989), the diary data at hand (which features repeated payments by the same person, see Appendix A.2) show that it's very common for the same individual to pay for a small purchase using cards and for a large one using cash, depending on the level of cash they hold at each point in time. This shows that people do not follow simple *transaction-size threshold* policies, settling small payments in cash and big ones with cards, and suggests a more complex behavior. As for Alvarez and Lippi (2017), Figure 1 clearly shows that it's possible that agents use their cards when cash on hand is sufficient to carry out the transaction: it seems that cash does not *always* burn in the hands of consumers. I call this kind of behavior *voluntary* cashless usage. A simple explanation for this could be heterogeneity in tastes: some individuals just prefer to use cashless methods, as they are fast and easy to use; they bring cash with them in case they meet a shop that does not accept cards, but whenever they have the chance (even if cash balances are sufficient) they pay cashless. The data at hand, however, seems to rule out this simple explanation. If taste heterogeneity was entirely driving voluntary cashless usage, the probabilities in Figure 1 shouldn't exhibit any kind of dependence on m and s: why would people that only care about their time-invariant taste for cash versus cards take different decisions depending on the level of cash holdings, or on the size of the transaction? The fact that the intensity of voluntary cashless usage depends on these determinants suggests that there is some fundamental reason related to cash management that generates this kind of behavior, a mechanism that the theory of Alvarez and Lippi (2017) cannot study as their transactions are infinitesimal, as the authors themselves acknowledge. Further evidence about this is provided in Appendix A.2, where I display the analogue of Figure 1 after having restricted the sample to individuals that reportedly prefer to use cash or are indifferent between cards and cash. A very similar pattern emerges also for these individuals, strengthening the claims I made above.

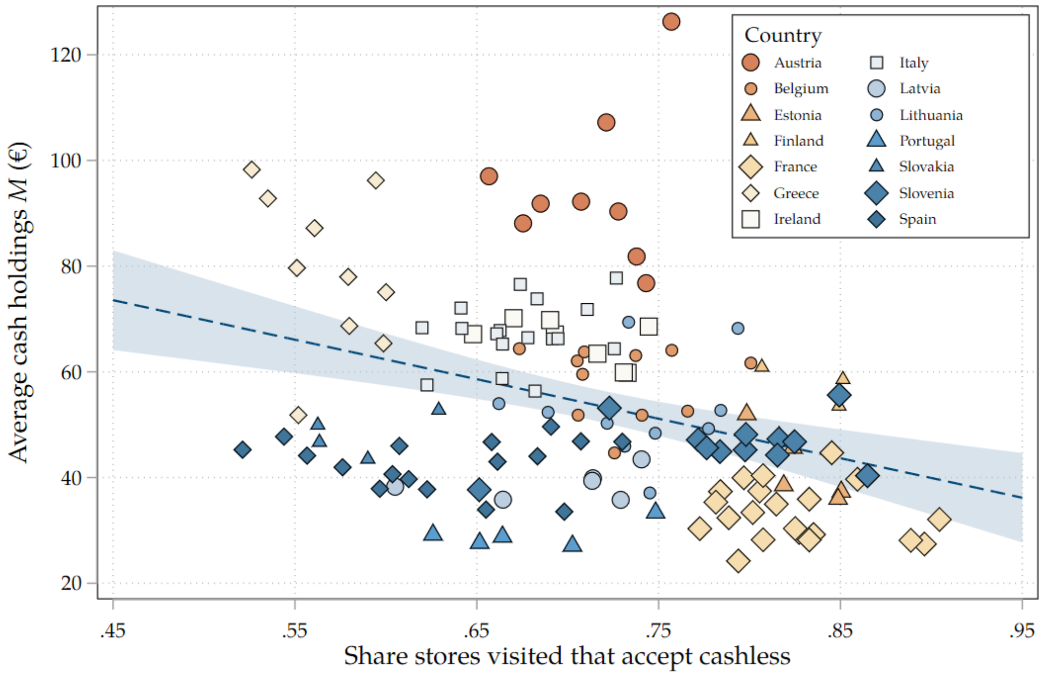
2.3 The role of imperfect cashless acceptance

Existing models of payment choices and cash management do not take into account the fact that cashless methods are not universally accepted.[5] This omission could lead to theoretical results which are not coherent with observed behavior, for two reasons: i) imperfect cashless acceptance introduces a precautionary motive for holding cash; ii) payment choices are influenced by card acceptance levels. I now provide evidence on these mechanisms.

First, I consider the association between imperfect cashless acceptance and the level of cash holdings. If cards are not universally accepted as a means of payment, consumers know that they may encounter a situation in which i) they don't have enough cash with them to settle a transaction; ii) the store does not accept their cashless payment method. One would expect that, in response to this, agents will optimally hold more cash in order to relax their cash-in-advance constraints. In other words, where cashless acceptance rates are lower, people have a stronger *precautionary motive* for holding cash. Figure 3 suggests that this mechanism is actually in place. In the Figure, I plot average cash holdings and cashless acceptance rates for each NUTS 2 level region in SUCH

[5]In Alvarez and Lippi (2017), the authors explicitly acknowledge the importance of cashless acceptance (and including transaction sizes too) for modeling cash/cashless choices, saying that "future models might benefit by unifying those aspects into a single model and quantify the relative importance of each of these frictions by using the relevant micro data".

Figure 3: Average cash holdings and cashless acceptance rates in different Euro Area NUTS 2 regions.



Note: This graph plots, for each Euro Area region (NUTS 2 classification), average cash holdings in that region against the regional share of shops that accept cashless payments. A linear fit with 95% confidence intervals is overlaid to the graph. *Source: ECB SUCH (2016) Data.*

data. The plot shows that in regions with high cashless acceptance rates, agents hold less cash[6]. This seems to confirm that there exist a precautionary motive for holding cash related to uncertainty over future acceptance of alternative payment methods.

Fact 3. *In areas with lower rates of cashless acceptance, agents hold more cash.*

Perceived rates of acceptance of cashless instruments may also affect payment behavior. Agents could decide on how to pay based on acceptance rates they expect to encounter in future payments. To see why, think of two consumers, a and n: both endowed with a cashless instrument (say a debit card). Both prefer to settle their purchases in cash, but still use the card when they run out of cash. Suppose that both consumers are currently facing two identical purchases that they can settle using whichever payment instrument they like, since they are visiting a shop that accepts both payment methods and they have sufficient cash. However, n believes that for her next payment in the next payment cashless methods will not be accepted (for instance, because she plans

[6]Notice that this is not a causal statement but just the description of an observed correlation. One cannot use this approach to make causal statements on the effect of an increase in cashless acceptance on cash holding behavior, as reverse causality is a legitimate concern here. Indeed, merchants strategically decide on whether to accept cashless payments or not depending on how much cash people hold in their area, a result I plan to explore in detail in a recently started project (Moracci and Sorbera (2022)).

TABLE 2: Linear probability model - Expected acceptance for next transaction and payment choices.

	Dependent variable: $Cashless_{it}$			
	OLS	OLS	OLS	FE
	(1)	(2)	(3)	(4)
Expected acceptance rate	0.26***	0.13***	-0.0099	-0.049*
	(0.012)	(0.016)	(0.016)	(0.022)
Observations	33259	20510	20484	20484
Only vol. payments		✓	✓	✓
Controls			✓	✓

Note: I only use the most recent SPACE data as SUCH does not contain the urban/rural information, which is crucial for acceptance rates.

to visit a type of store where cards are not commonly accepted, such as a cigarettes shop); on the contrary, a is much more confident that cards will be accepted even in her next shopping trip to the local gas station. Given that holding cash has a higher precautionary value for n in this situation (she is not sure of being able to use the card in her next purchase, therefore she wants to avoid running out of cash), we expect her to use cashless payments with a higher probability than a, in order to preserve cash for her incoming payment. This hypothesis is not trivial to test, given that of course I don't observe expectations on cashless acceptance for future transactions. However, if agents are rational, expected levels of acceptance should be in line with observed ones, given that agents are expected to have information on the characteristics of their incoming purchases (transaction size, type of store) and on the distribution of acceptance policies in their geographical zone. I estimate the model

$$CashlessAccepted_{i,t} = \alpha + \gamma \mathbf{X}_{it} + \eta \mathbf{D}_i + \epsilon_{i,t}, \tag{1}$$

where i denotes an individual and t denotes a transaction, $\mathbf{X}_{it}$ is a vector of controls that depend on the specific transaction (size of the purchase, type of store), while $\mathbf{D}_i$ is a vector of controls that depend on the individual, such as demographics (age, sex, education), which are expected to be a predictor of *search* for shops that accept different payment methods (old people are more likely to visit stores that don't accept cards), location (NUTS-2 level province and urban/rural density) and preferences (survey responses on preferred payment methods). After estimating such model, for each transaction (i, t), I compute the expected probability of acceptance for the next purchase

$(i, t+1)$[7], given by fitted values of (1)

$$ExpFutAccept_{i,t} = \widehat{CashlessAccept}_{i,t+1},$$

and then I estimate the linear probability model

$$Cashless_{i,t} = \beta_0 + \beta ExpFutAccept_{i,t} + \mathbf{X}_{i,t} + \varepsilon_i + \nu_{i,t} \tag{2}$$

where $Cashless_{i,t}$ is a dummy equal to one if individual i settled her tth transaction using cashless methods. I again control for transaction-specific and I either include individual-specific characteristics or individual fixed-effects. Estimation results are displayed in Table 2. When no controls are included and all the observations are taken into account, the relationship between expected cashless acceptance and the likelihood of a cashless payment seems strongly positive. Part of this effect, however, is due to selection: by focusing only on voluntary payments, where both payment methods were available to the consumer (as it is much more likely that cashless was not even an option for people that, for instance, live in a low-acceptance area), the magnitude of the positive association between expected acceptance rates and cashless intensity shrinks. Including individual-specific and transaction-specific controls, the relationship becomes insignificant, and once estimating a model which fixed effects to deal with the problem of unobserved heterogeneity, it switches sign, as expected. In particular, I estimate that a 20-percent decrease in the expected acceptance rate for the incoming payment (when both options are available) increases the probability of a voluntary cashless transaction of 1 pp.

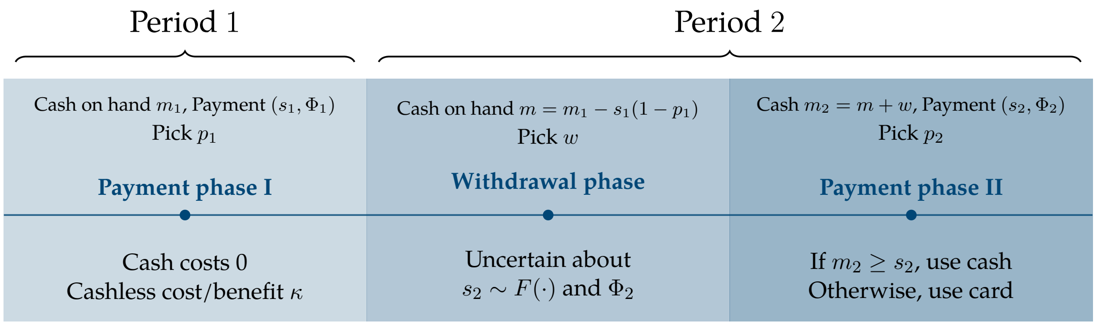
Fact 4. *Voluntary cashless payments are more frequent when expected cashless acceptance for future transactions is lower.*

3 A stylized two-period model

In this Section, I present a simple, two-period model that rationalizes the above findings and provides further insights. The model features payment method choices in a dynamic cash management setting (as in Alvarez and Lippi (2017)), the presence of uncertain discrete-sized expenditures (as in Whitesell (1989)) and imperfect acceptance of cashless methods. In the model, I focus on agents that prefer paying by cash. Results are easier to obtain and hold *a fortiori* also when agents prefer to use cashless methods, but the model solution for them is less interesting. I will of course take this type of individuals into account in the quantitative model.

[7] Of course, it is not possible to estimate this probability for the last transactions reported in the payment diary by each individual, as there is no information on the next purchase.

FIGURE 4: Timing of the two-period model.



3.1 Model setup

Consider the problem of an agent that lives for two periods. In each period, she needs to make a purchase whose size s is exogenously drawn from a probability distribution with CDF $F(s)$. She has access to two payment methods: cash and a cashless payment method (say a debit card). At the start of the second period, cash can be withdrawn from ATMs[8] paying the fixed cost $b > 0$. Holding m units of cash during each payment phase entails a variable cost Rm. Settling a transaction with the cashless method entails a fixed cost $\kappa > 0$, relative to doing so using cash. Stores are of two types $\Phi \in \{a, n\}$, with $\Pr(a) = \phi$: stores of type a accept cashless payments, while stores of type n don't[9]. When entering a store of type n with cash on hand lower than the size of the purchase, agents lose the possibility to settle the transaction and face an utility cost u. In the first period, the agent discounts period-2 utility at rate $\beta \in (0, 1)$.

Let m_1 denote the amount of cash on hand when carrying out the first payment, m denote the amount of cash left after the first payment and m_2 denote the amount of cash holdings when facing the second payment. Additionally, let s_t denote the size of the transaction in period t, and $\Phi_t \in \{a, n\}$ denote the type of store visited at time t. Let p_t denote payment method choices in period t, i.e., $p_t = 1$ if the payment of period t was settled using cashless methods and $p_t = 0$ if cash was employed. Let w denote the amount of cash withdrawn between the two payments. Finally, let l_t denote lost purchases: in particular, $l_t = 1$ means that the purchase at time t was lost due to insufficient cash holdings and lack of cashless acceptance.

Figure 4 illustrates the timing of the model. Based on the value of m_1 and on the size of the transaction s_1, agents have to choose whether to pay with cards or with cash. This applies only if they have both options available, i.e., when $s_1 < m_1$ and $\Phi_1 = a$:

[8] I make the simplifying assumption that cash cannot be deposited. This assumption is justified by the structure of the model. To see why, think of an infinite version horizon of this model. Notice that except for initial cash holdings m_1 (which are exogenously assigned), there are no exogenous inflows of cash. All cash that agents have on hand has been obtained by paying the fixed cost b, and it cannot be optimal to pay the fixed cost again to deposit it. In a steady state of such model, as soon as the effect of high initial cash holdings m_1 has vanished, there are no deposits.

[9] For the moment, I assume that cash is universally accepted; this assumption will be relaxed in the quantitative model.

when $\Phi_1 = a$ but cash on hand m_1 is not enough, agents need to use their cards; when m_1 is sufficient but $\Phi_1 = n$, they need to use cash; when m_1 is scarce and $\Phi_1 = n$, they lose the purchase. Depending on the payment method chosen, the amount of cash m held after the first payment is given by $m = m_1 - s_1(1 - p_1)$. Afterwards, agents have the opportunity to adjust cash holdings to $m_2 = m + w$ by paying the fixed adjustment cost b and withdrawing $w > 0$. Then, s_2 and Φ_2 realize and agents must decide on how to pay for their last purchase.

The problem that agents have to solve is a dynamic cost minimization problem given by

$$\begin{aligned} \min_{\{p_1,w,p_2\}} \quad & \mathbb{E}_{\{s_t,\Phi_t\}_{t=1,2}} \left[\kappa \mathbb{1}_{\{p_1=1\}} + b\mathbb{1}_{\{w>0\}} + \beta \left(Rm_2 + \kappa \mathbb{1}_{\{p_2=1\}} + u\mathbb{1}_{\{l_2=1\}} \right) \middle| \, m_1 \right], \\ \text{subject to} \quad & m_2 = m_1 - s_1 \cdot (1 - p_1) + w \\ & (m_t - s_t)(1 - p_t)\mathbb{1}_{\Phi_t=a} \geq 0, \ \forall t, \\ & (m_t - s_t)(1 - l_t)\mathbb{1}_{\Phi_t=n} \geq 0, \ \forall t. \end{aligned} \tag{3}$$

where w is the size of the adjustment performed at the end of the first period and p_t is equal to one if the payment of period t was settled with cashless methods and equal to zero otherwise. Notice that the second constraint imposes that cashless methods *have to* be employed when the size of the transaction is bigger than cash holdings and the store visited accept cards, whereas the third constraint imposes that if cash is scarce and the store visited does not accept cards a lost purchase arises. Let V_t denote the value function in the payment phase of period t, and V denote the value function in the adjustment phase. In the payment phase of period 2, the expected value of the problem for an agent with cash on hand m_2 facing a payment of size s_2 is given by

$$V_2(m_2, s_2) = Rm_2 + (1 - F(m)) \left(\phi\kappa + (1 - \phi)u \right), \tag{4}$$

i.e., in this period agents pay cash holding costs with certainty, but they might also pay other costs depending on the size of the purchase relative to cash holdings and on the type of store visited. The value of the problem in the withdrawal phase of the second period with $\tilde{m}$ units of cash holdings left after the first payment is given by

$$V(m) = \min \left\{ \mathbb{E}_{s_2} \left[V_2(m, s_2) \right] \ , \ b + \min_{m_2} \mathbb{E}_{s_2} \left[V_2(m_2, s_2) \right] \right\}. \tag{5}$$

Finally, in the payment phase of the first period, the value of the problem for an agent with m_1 units of cash on hand facing a transaction of size s_1 in a shop that accepts cards is given by

$$V_1(m_1, s_1) = Rm_1 + \begin{cases} \min\{\beta V(m_1 - s_1), \beta V(m_1) + \kappa\} & \text{if } m_1 \geq s_1, \\ \beta V(m_1) + \kappa & \text{if } m_1 < s_1. \end{cases} \quad (6)$$

The problem at time 1 for agents matched to shops that do not accept cards is trivial and not very important.

3.2 Model solution

I now outline the most important properties of the model's solution. First, I need to make a parametric assumption that it's needed to generate interesting results.

Assumption 1. *The cost of losing a purchase is higher than the cost of using the card, i.e.,* $u > \kappa$.

The above Assumption seems reasonable: it makes sense to assume that people prefer to use cards, even if they don't particularly like them, than leave the shop without completing the purchase.

I start from the payment choice in period 2 and move backwards. As there is no continuation value, however, this last choice is a trivial one: as $\kappa > 0$, agents will pay cash as long as $m_2 \geq s_2$, and use cashless payments only if cash on hand is insufficient, provided that cashless payments are accepted. If $m_2 < s_2$ and $\Phi_2 = n$, agents will lose the purchase. How much cash would an agent like to hold in payment phase 2? To answer, I must to derive optimal money holdings in the payment phase of period 2, i.e., I have to solve

$$m^* = \arg\min_{m_2} \mathbb{E}_{s_2}\left(V_2(m_2, s_2)\right) = \arg\min_{m_2} Rm_2 + (1 - F(m_2))\,\kappa.$$

The amount m^* is the one agents would like to have in their last payment phase from an *ex-ante* perspective, before knowing the realization of the second transaction size s_2. If individuals were given the chance to withdraw cash for free in the withdrawal phase, they would refill their wallet up to m^* immediately.

Proposition 1. *Ex-ante optimal money holdings at in the payment phase of period 2 are given by*

$$m^* = \begin{cases} f^{-1}\left(\frac{R}{\phi\kappa + (1-\phi)u}\right) & \text{if } \phi\kappa + (1-\phi)u > R/f(0), \\ 0 & \text{if } \phi\kappa + (1-\phi)u \leq R/f(0). \end{cases} \quad (7)$$

Proof. See Appendix B. ■

The result is intuitive: as f^{-1} is decreasing, the optimal amount of cash to hold is decreasing in R and increasing in κ and u. If the weighted sum of κ and u is low enough, agents don't want to hold any cash in the last payment phase. This happens also when it's too costly to carry cash around (large R) or if expected payments are so large that holding cash is most likely useless (low $f(0)$, which implies high $\mathbb{E}(s_2)$). Also notice that, consistently with Fact 3, m^* is decreasing in ϕ, the level of cashless acceptance.

I now focus on the previous choice: whether to adjust or not in the adjustment phase for given cash on hand m. For simplicity and without loss of generality, I assume that $m \leq m^*$, i.e., that no one holds more cash than the period-2 optimal quantity in the adjustment phase[10]. Then, notice that by substituting m^* in (5) one gets,

$$V(m) = \min \left\{ \begin{array}{l} Rm + (1 - F(m)) \left(\phi\kappa + (1-\phi)u\right), \\ b + Rm^* + (1 - F(m^*)) \left(\phi\kappa + (1-\phi)u\right) \end{array} \right\}$$

Trivially, if $\phi\kappa + (1-\phi)u \leq R/f(0)$ it's never optimal to pay b in order to adjust to $m^* > m$ by withdrawing cash, as they have $m^* = 0$. When instead, $\phi\kappa + (1-\phi)u > R/f(0)$, it is optimal to withdraw when

$$b + R(m^* - m) < (F(m^*) - F(m)) \left(\phi\kappa + (1-\phi)u\right),$$

i.e., when the cost of adjusting and the discounted increase in holding cost due to higher cash holdings are smaller than the expected discounted savings in payment costs, induced by a lower probability of forced card usage for the second payment. The next Proposition gives a more precise characterization of optimal withdrawal policies.

Proposition 2. *Let $\bar{b}$ be given by*

$$\bar{b} = F(m^*) \left(\phi\kappa + (1-\phi)u\right) - Rm^*.$$

The following results hold:

1. *If $\phi\kappa + (1-\phi)u \leq R/f(0)$, $w(m) = 0$ for all $m \in [0, m^*]$;*
2. *If $\phi\kappa + (1-\phi)u > R/f(0)$ and $b \geq \bar{b}$, , $w(m) = 0$ for all $m \in [0, m^*]$;*
3. *If $\phi\kappa + (1-\phi)u > R/f(0)$ and $b < \bar{b}$, there exists $\overline{m}$ given by the unique solution to*

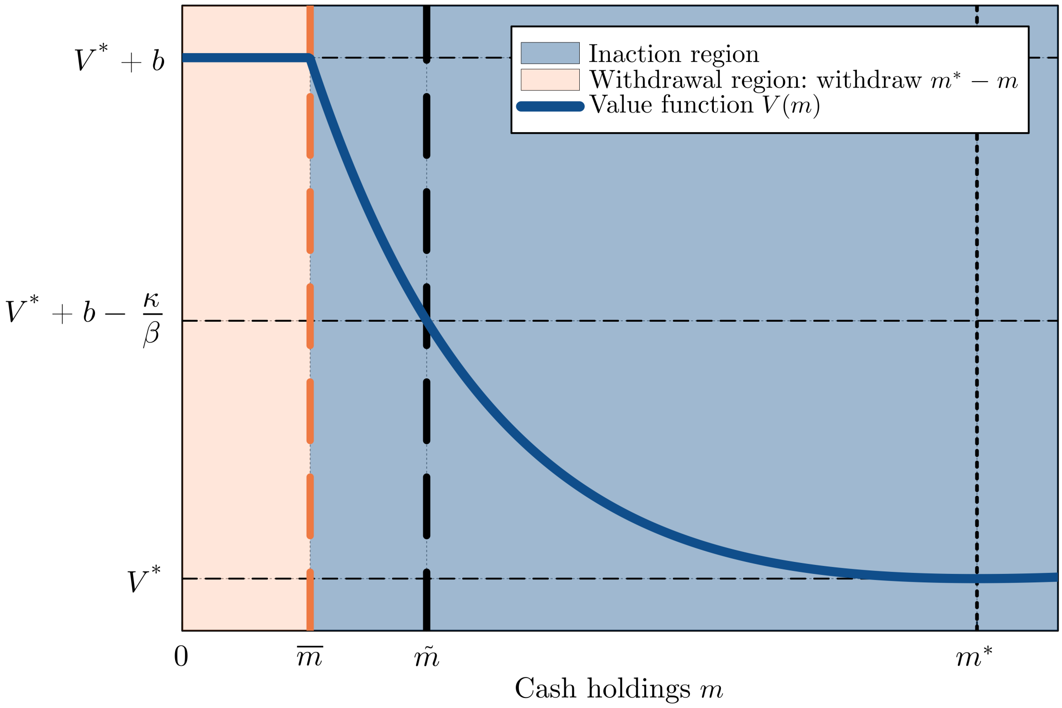
$$R\overline{m} - F(\overline{m}) \left(\phi\kappa + (1-\phi)u\right) = Rm^* - F(m^*) \left(\phi\kappa + (1-\phi)u\right) + b,$$

such that $w(m) = m^* - m$ for all $m \in [0, \overline{m}]$ and $w(m) = 0$ for all $m \in (\overline{m}, m^*]$.

Proof. See Appendix B. ■

[10] A simple way to obtain this is to assume that $m_1 < m^*$ for all agents. As specified in the previous Footnote, it makes sense to restrict to this case to avoid deposits that would occur just because of arbitrarily high initial cash holdings, and not as a consequence of sequences of choices.

FIGURE 5: Value function $V(m)$ and withdrawal policy $w(m)$ - Exponential case



The above Proposition says that, when the cost of withdrawing is relatively low with respect to the expected costs due to cashless payments and lost purchases, there exist an interval of low cash holdings $[0, \overline{m}]$ such that agents whose cash holdings fall in this interval after the first payment prefer to withdraw cash and reset their wallets to m^*. Figure 5 displays the shape of the value function $V(m)$, the inaction and withdrawal regions and the trigger and target levels $\overline{m}$ and m^* for the case of an exponential transaction size distribution $(F(s) = 1 - \exp(-\lambda s))$.

I can therefore rewrite the value function in the withdrawal phase of the second period in the following way. For the interesting case $b \leq \overline{b}$, I have that

$$V(m) = \begin{cases} b + V^* & \text{for } m \in [0, \overline{m}], \\ Rm + (1 - F(m))\,(\phi\kappa + (1-\phi)u) & \text{for } m \in (\overline{m}, m^*]. \end{cases} \tag{8}$$

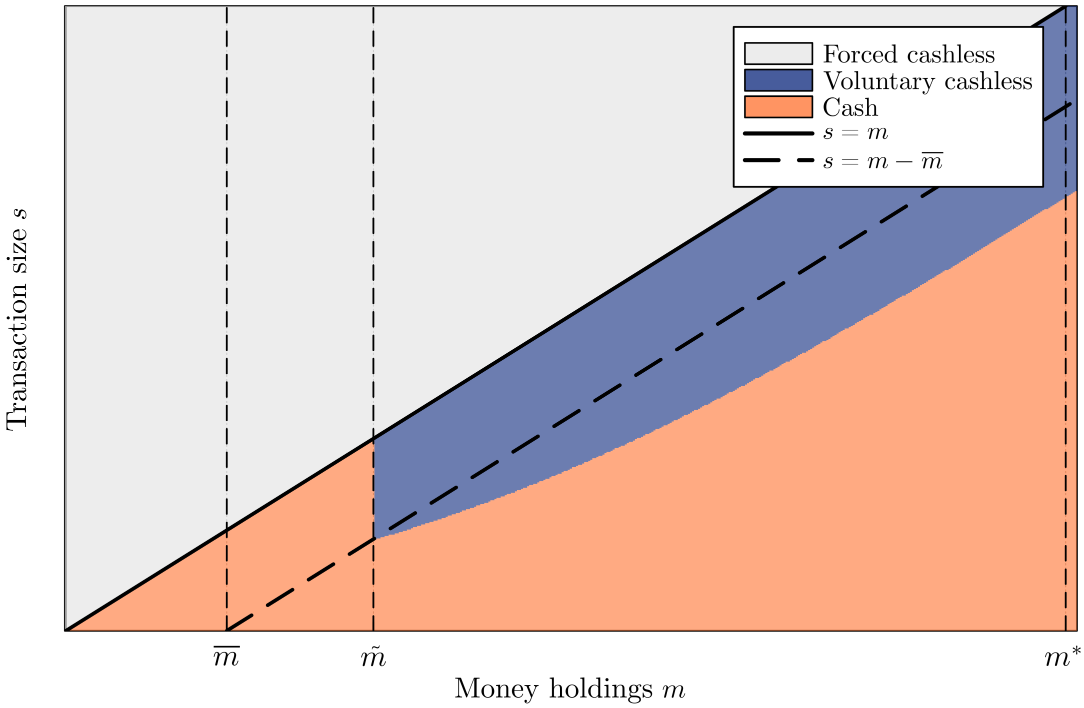
where

$$V^* = Rm^* + (1 - F(m^*))\,(\phi\kappa + (1-\phi)u)\,.$$

I finally analyze payment choices at $t = 1$. I focus on the non-trivial case of $m_1 > s_1$ and $\Phi_1 = a$, as agents will be forced to either use their cards or cash in other situations. The relevant situation I want to analyze is characterized by a non-degenerate payment choice set, so that observed payment choices are *voluntary*. In particular, I want to investigate whether card usage could be optimal even when agents are able to pay using cash. For this particular region of (m_1, s_1) and assuming $b < \overline{b}$, I can write the

FIGURE 6: Payment choice policies $p(m, s)$ in period 1 - Exponential case

Note: the solid (dashed) black line represents the locus $s_1 = m_1$ ($s_1 = m_1 - \overline{m}$).



value of the problem in the following way.

$$V_1(m_1, s_1) = Rm_1 + \begin{cases} \min\left\{\beta\left(V^* + b\right), \beta\left(V^* + b\right) + \kappa\right\} & \text{if } m_1 \leq \overline{m}, \\ \min\left\{\beta V(m_1 - s_1), \beta V(m_1) + \kappa\right\} & \text{if } m_1 > \overline{m} \wedge s_1 < m_1 - \overline{m}, \\ \min\left\{\beta\left(V^* + b\right), \beta V(m_1) + \kappa\right\} & \text{if } m_1 > \overline{m} \wedge s_1 > m_1 - \overline{m}. \end{cases} \quad (9)$$

There are three cases. First, when cash holdings are very low, i.e. $m_1 < \overline{m}$, agents will have to withdraw in the next payment phase, no matter how small or large s_1 is or whether they pay by cash or cards. When cash holdings are above the withdrawal level $\overline{m}$, instead, agents could be led to withdraw in the next period or not, depending on the size of the first period transaction and on their payment method choices. In particular, if the incoming payment is such that $s_1 < m_1 - \overline{m}$, they will not need to withdraw in the withdrawal phase of the second period even in case of a cash payment, as cash balances in the withdrawal phase would be $m = m_1 - s_1 > \overline{m}$. If, on the contrary, agents with $m_1 > \overline{m}$ face a payment such that $s_1 > m_1 - \overline{m}$, they will have to withdraw in the next period if they choose to pay by cash, as they would remain with only $m = s_1 - m_1 < \overline{m}$ units of cash on hand. The following Proposition describes optimal payment choices in the first period.

Proposition 3. *Let $\phi\kappa + (1 - \phi)u \geq R/f(0)$ and $b \leq \overline{b}$.*

1. *Let $\kappa \geq \beta b$. For any $m_1 \in [0, m^*]$, then $p_1(m_1, s_1) = 0$ for any $s_1 < m_1$.*

2. *Let $\kappa < \beta b$. Then, there exists $\widetilde{m}_1 \in (\overline{m}, m^*)$ implicitly given by*

$$V(\widetilde{m}_1) = V^* + b - \frac{\kappa}{\beta} \tag{10}$$

such that

(*a*) *If $m_1 \in [0, \tilde{m}_1]$, then $p(m_1, s_1) = 0$ for any $s_1 < m_1$, i.e.,* cash-poor *agents settle their transaction with cash if they have enough.*

(*b*) *For any $m_1 \in (\tilde{m}_1, m^*]$, there exists a nonempty convex set of transaction sizes $S(m_1) = [\underline{s}(m_1), m_1]$ such that $p_1(m_1, s_1) = 0$ for any $s_1 \in S(m_1)$, i.e.,* cash-rich *agents settle transactions above a certain threshold (that depends on the level of cash holdings m_1) with cards. Moreover, $\underline{s}(m_1) \leq m_1 - \bar{m}$.*

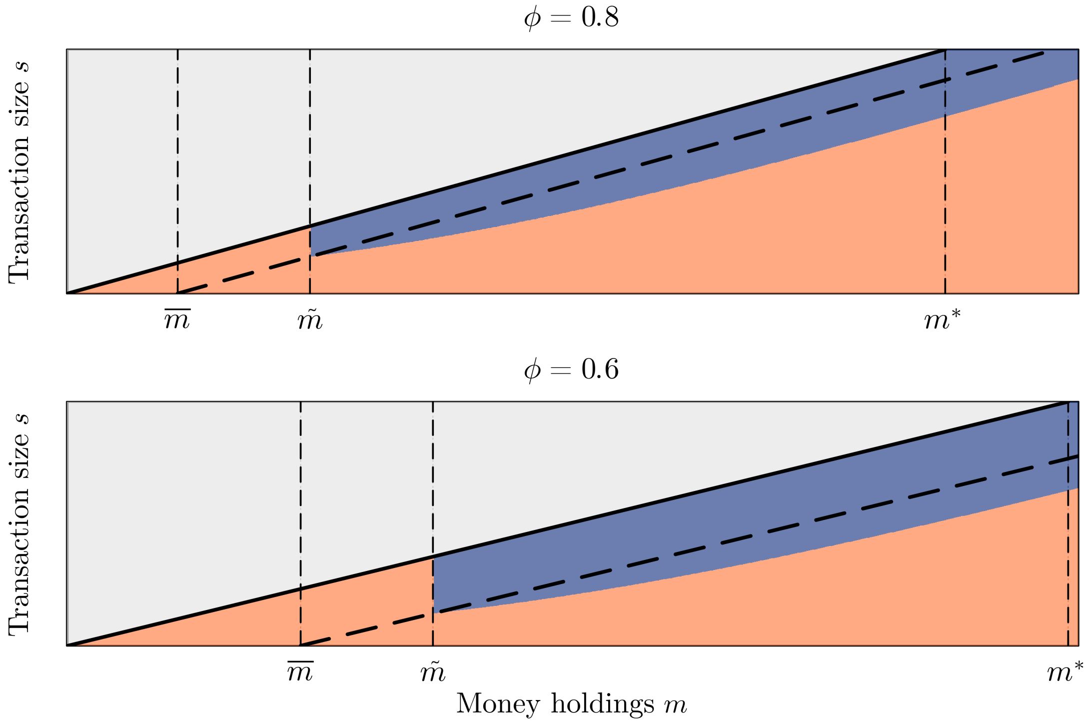
Proof. See Appendix B. ■

The above Proposition shows that even when $\kappa > 0$ it can be optimal to pay cashless for a certain region of cash holdings m_1 and transaction sizes s_1. This happens when current cash holdings are large enough $(m_1 > \widetilde{m}_1)$ and the transaction size is big enough *relative* to cash holdings $(s_1 > \underline{s}(m_1))$. Indeed, when cash holdings m_1 are sufficiently close to the optimal level m^* and the incoming payment is large enough to deplete them, agents can find optimal to use their cards in order to save cash for future shopping trips in shops where cashless methods might not be accepted. As displayed in Figure 6, this happens every time that $m_1 > \widetilde{m}_1$ and $s_1 > m_1 - \overline{m}$, i.e., when payments are big enough to push agents in the withdrawal region at the start of the next period. While I proved that certainly $\underline{s}(m_1) \leq m_1 - \overline{m}$, I cannot exclude that $\underline{s}(m_1)$ is strictly smaller than $m_1 - \overline{m}$: depending on parameter values, it could be optimal to pay cashless even for some points (m_1, s_1) with $s_1 < m_1 - \overline{m}$. Figure 6, where I plot the payment choice policy function $p(m_1, s_1)$ for the case of an exponential transaction size distribution $(F(s) = 1 - \exp(-\lambda s))$, shows that this is actually the case for some parametrizations. It is easy to show that this happens when $(1 - \phi)u$ is large enough: if agents are really concerned about losing the possibility to carry out a transaction (because this it is highly likely to encounter a merchant who doesn't accept cards or because the cost of losing a purchase is very high) they will use their cards instead of cash even when the purchase is not large enough to push them inside the withdrawal region in the second period.

The economic intuition for these optimal policies is simple: individuals compare the extra cost of a cashless payments κ with the difference in expected costs $\Delta V(m, s) = \beta(V(m) - V(m - s)) < 0$ induced by a cash payment: they decide to pay using cashless only if the reduction in expected future cash management cost is high enough to compensate for the extra transaction cost κ. Of course, when s is very small, $\Delta V(m, s) \simeq 0$, so it's never worth it to pay κ, as the future cash management benefits are minimal.

FIGURE 7: The effect of a decrease in ϕ - Exponential case

Note: the solid (dashed) black line represents the locus $s_1 = m_1$ ($s_1 = m_1 - \overline{m}$).



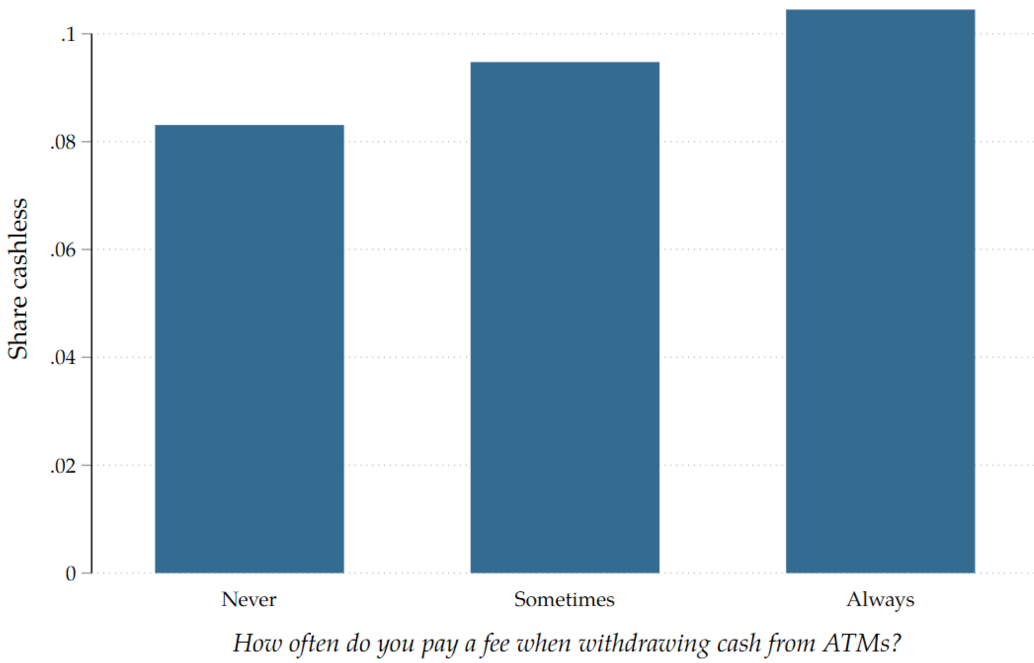
Notice that these optimal policies are consistent with the evidence presented in Figure 1, where the bulk of voluntary cashless payments was concentrated in a region characterized by high m and s very close to m.

Moreover, an additional implication of the model is that voluntary cashless usage by agents that prefer cash payments is a consequence of imperfect acceptance. As shown in Figure 7, the lower is ϕ, the larger is the region of the relevant state space $[\overline{m}, m^*]$ for which voluntary cashless usage is optimal, consistently with Fact 4. As more shops start accepting cashless methods, the precautionary motive for holding cash decreases and it is less convenient to pay with the card in order to insure against future shortages. In other words, in a world with perfect card acceptance, only those who really prefer paying with cards decide to use them.

3.3 Cashless payments as a cash management tool: empirical evidence

A novel finding is that agents can voluntarily use cards even if this entails a cost with respect to cash usage, as long as cashless payments are *cheaper* with respect to withdrawals, i.e., when κ is smaller than the discounted withdrawal cost βb. In this model, cashless payments are sometimes employed as a *cash management tool*: agents strategically use their cards when they want to preserve their cash holdings, in order to avoid costly trips to ATMs in the future. This simple analytical model has a sharp predic-

Figure 8: Withdrawal costs and voluntary cashless payments.



Note: Information on usual withdrawal costs faced by consumers is obtained from answers to the question "*How often do you have to pay fees when withdrawing at ATMs?*". An higher likelihood of paying fees when withdrawing is a proxy of higher withdrawal costs b. I only consider voluntary payments, and I restrict the sample to people who reportedly prefer to use cash, to keep κ fixed while b varies. *Source: ECB SUCH Data (2016).*

tion: voluntary cashless usage by agents who dislike using cards is possible only when the fixed cost of a cashless payment is lower than the discounted fixed cost of an ATM withdrawal.

This prediction is not easily testable as neither κ nor b are observed in the data. However, if one is willing to make some assumption about the relationship of κ and b with observables, it is possible to obtain some insights. As our measure of κ I can exploit the fact that both in SUCH and in SPACE survey questionnaires individuals are asked about their preferred payment method. I focus on agents that reportedly prefer cash, so that $\kappa > 0$ (as in the model) seems a reasonable assumption. Ideally, one would like to keep κ fixed and see how the share of voluntary cashless payments changes with b. As a proxy for b, I exploit the answer to the question "*How often do you have to pay fees when withdrawing at ATMs?*", which was asked in the SUCH survey (2016). Agents report if they never pay fees when withdrawing, if they sometimes have to pay or if ATM usage always entails the payment of a fee. In Figure 8 I display the share of voluntary payments which is performed using cashless methods as a function of the proxy for b. Results show that higher withdrawal costs are associated with a higher share of voluntary payments being settled using cashless methods, which is consistent with the theoretical implications of the model regarding the cash management role of card payments. When agents find it harder to withdraw money, they increase card usage to preserve higher cash balances, instead of using them and replenish at ATMs more often.

3.4 Relationship with previous work

I now highlight that some of the features of decision rules found by Whitesell (1989) and Alvarez and Lippi (2017) are also present in this model, i.e., that the optimal payment policies presented above can be thought of as a more general decision rules which include features of payment choice policies discussed in previous work on the topic.

A rationalization of transaction-size thresholds. As said before, the observed negative correlation between transaction sizes and frequency of cash usage motivated Whitesell (1989) to derive transaction-size threshold policy rules for payment choices: when the size of a payment is larger than the threshold $\bar{s}$, in his model, cashless payments are optimal. However, he derived his result under two assumptions: i) agents minimize the steady-state cost of policies, with no explicit dynamic optimization or uncertainty involved [11]; ii) the cost of using cashless methods depends on the size of the transaction, i.e., it has form $\kappa_0 + \kappa_1 s$. In the model presented in this paper, there is no need to assume that the cost of cashless payments depends on s or to transform set up the problem as static and deterministic to obtain payment choices that depend on the size of the transaction. In the model presented above, something very similar to transaction size threshold policies emerges naturally from the problem's dynamic structure, which makes agents internalize the consequences of their payment choices on expected cash management costs. For any level of cash holdings $m_1 > \widetilde{m}_1$, there exists an m_1-specific transaction size threshold $\underline{s}(m_1)$ and agents find it optimal to use cashless payments if $s_1 > \underline{s}(m_1)$. This can be seen as a generalization of the theory based on the existence of a unique transaction size threshold: thresholds are not only individual specific (as they depend on policy parameters which are clearly heterogeneous, such as κ or R): they are transaction-specific, as they depend on cash holdings.

A rationalization of cash burns policies. As said above, optimal policies in Alvarez and Lippi (2017) are the so-called *cash burns* policies. People pay in cash whenever they have enough (which in their setting means any time agents have $m > 0$, as the consumption stream is infinitesimal). (m, s) *policies* have a similar property: when s is

[11] Whitesell (1989) assumes that albeit transaction sizes are not all equal, the total amount spent in each period is fixed and so is the fraction of incoming transactions of each size. Therefore, in his setup agents just choose the total amount of cash to hold, and they never run out because expenditures can never exceed their expected value: the model is deterministic. It is also static, i.e., the evolution of m in response to different sequences of transaction sizes in a given period is not modeled: given full certainty, it is in fact irrelevant, as the average cash balances in all periods (and therefore opportunity costs) will be the same independently of the sequence in which expenditures come. This creates independence of decision rules with respect to m, as decisions are taken at the start of the period

lower than some threshold, it is never optimal to settle transactions using a cashless method. This is because the gain of using the card (avoiding a depletion in cash balances) is so low (as s is small, cash balances are relatively unaffected) that it's not worth it to pay the fixed cost κ. When s is extremely small, as in Alvarez and Lippi (2017) it is perfectly reasonable that agents prefer to use cash, as they do not push money holdings down and at the same time, they pay no cost.

4 A quantitative model

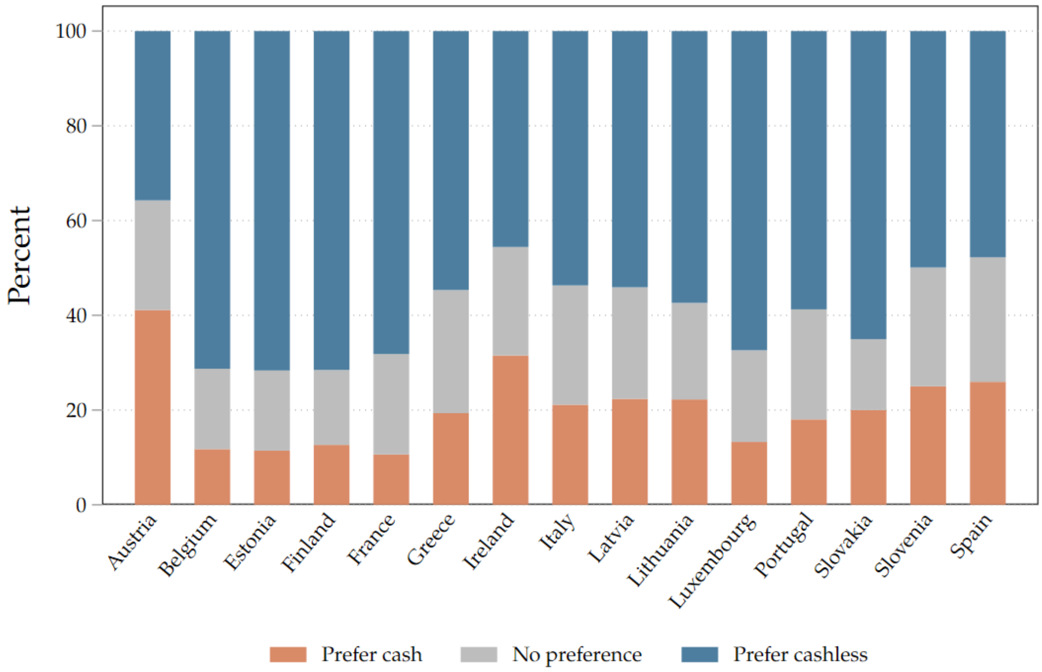
The model presented in the previous Section offered some insights on how people take their payment and cash management decisions and highlighted the importance of simultaneously including some features in the theory to avoid missing relevant determinants of behavior: the presence of multiple transaction sizes, uncertainty on the future stream of payments and on merchant acceptance are all important ingredients in shaping individuals' behavior. However, the above framework is not suitable for estimation or quantitative analysis, for multiple reasons. First, in the presented model choices are deterministic: for any vector of parameters, each point of the state space (m, s) maps to a single choice with certainty. This leads to a zero likelihood problem in estimation and prevents the model from matching the data. Second, some restrictions imposed to simplify the analysis are unlikely to hold in real settings and this could bias the estimation results. In the next Subsection I present evidence that suggests that a few additional channels must be included in a quantitative analysis to avoid this problem. Last, an extended model will enable me to perform a quantitative analysis of the determinants of heterogeneity in payment and cash management behavior across the Euro Area. In order to disentangle the differences due to preference heterogeneity from those generated by other factors (say, variation in merchant acceptance levels) I need the model to be flexible enough to allow for different conditions (price levels, payment frequencies, supply-side constraints) in different countries. An additional benefit of building such a model is that, after estimation, this tool can be used to give quantitative answers to policy-relevant questions.

4.1 Towards a quantitative model: additional elements

The quantitative framework features three important additional elements with respect to the simple analytical model: heterogeneity in tastes for cashless payments, imperfect acceptance of cash payments and information on the size of incoming purchases.

Payment preferences. The data contain rich information on payment preferences of individuals obtained via survey questionnaires. In both surveys, respondents were asked to choose their preferred payment method. They could pick one of the following responses: *cash*, *no preference* or *cashless*. Answers to this question for the year 2019

FIGURE 9: Payment preferences.



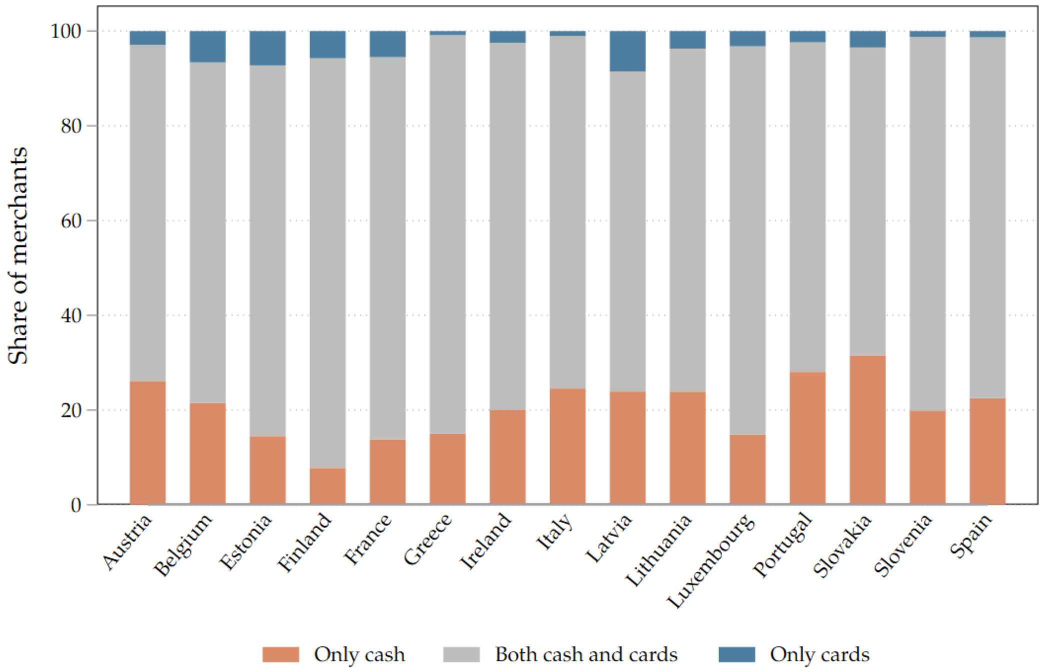
Note: This graph plots the answers to the questionnaire question *"If you were offered various payment methods in a shop, what would be your preference?"* for all countries in the survey, both for SUCH (2016) and for SPACE (2019). The options were cash, a generic cashless option and the absence of a preferred payment method. The plot is based on data for a total of 65,858 respondents.
Source: ECB SPACE (2019) Data.

(SPACE data) are reported in Figure 9. As the Figure shows, the appreciation for cashless payments has been growing in recent years and they are now reportedly preferred to cash in many countries[12]. More importantly, what emerges from Figure 9 is that there is sizeable within-country variation in preferences. Incorporating these differences across individuals in the model is crucial to disentangle voluntary cashless usage induced by preferences from that induced by cash management concerns: as the welfare implications of these two kinds of behavior are clearly different, it's important to understand how often the card is used because people like to do so and how often it is used because people decide to do it (despite they don't like it) to save cash for future shopping trips where cards could be not accepted. It is also important in order to have non-degenerate payment choice probabilities: for each transaction characterized by (m, s), there will be a distribution of possible choices induced by heterogeneity in tastes across households.

Merchant acceptance. As I showed in Subsection 2.3, rates of cashless acceptance by merchants are an important determinant of cash management and payment behavior.

[12]In 2019 data, Austria is the only country in which there were more respondents saying that they prefer cash than respondents saying that they prefer cashless payments.

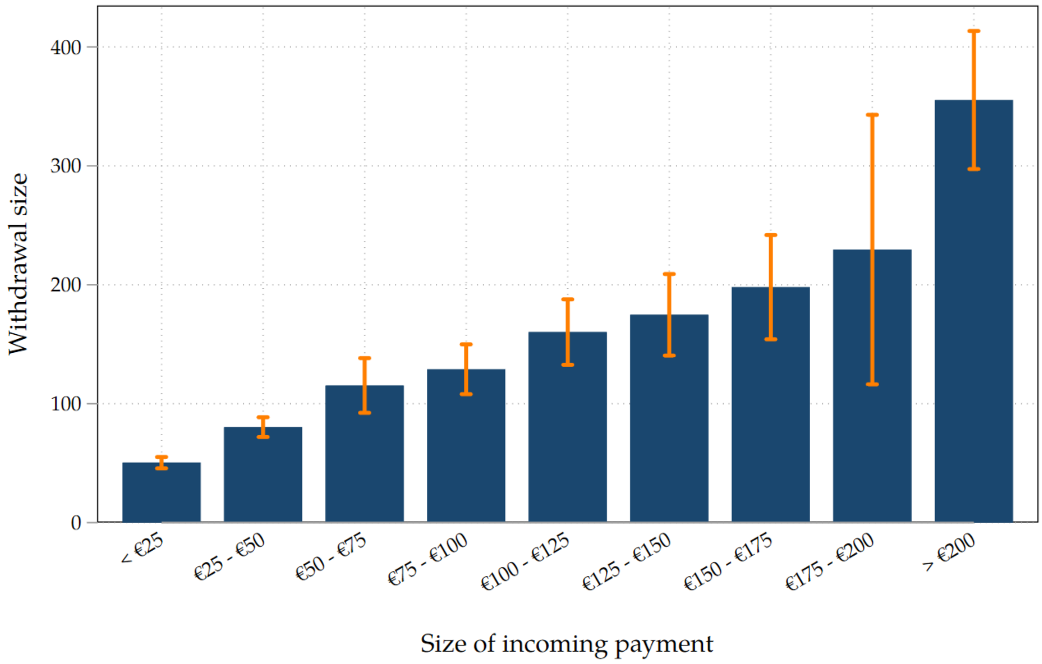
FIGURE 10: Merchant acceptance, shares by country.



Note: This graph plots the share of merchants that accept only cash, only cards or both, for each Euro Area country in the sample. Shares are computed combining observed payment choices with information provided by respondents on the acceptance policies of each merchant they visited. *Source: SPACE (2019) Data.*

Ignoring supply-side constraints such as limited acceptance while modeling payment and cash management choices can be still acceptable in settings where the extent on non-acceptance is very limited (as in the US setting studied by Briglevics and Schuh (2021)), but it would lead to very biased results in the Euro Area, where the share of merchants not accepting cards is sizeable in many countries, as Figure 10 shows. In the stylized model presented in the previous Section, I allowed for imperfect acceptance of cashless payment methods but I still assumed for simplicity that cash was always accepted. While this assumption was totally fine until a few years ago, Figure 10 shows that it might start to lose adherence to reality. In the payment diary of SPACE, agents were asked if cash was accepted in each point of sale where they performed a cashless purchase. The availability of this additional information enables me to estimate which share of shops in each country accepted only cashless as a payment method. Combining it with information on imperfect acceptance of cards, for each country I can derive the share of merchants that fall in each of three categories: those who accept only cash, those who accept only cards, those who accept both. Despite still small, the share of merchants that only accept cards has become non-negligible in many countries; it is important to take this into account in order to avoid labeling some choices to use the card as voluntary while they are potentially motivated by supply-side constraints.

FIGURE 11: Withdrawals and sizes of incoming purchases.



Note: This graph the average size of withdrawals w_{it} (conditional on having withdrawn, i.e., $w_{it} > 0$) for different levels of transaction sizes s_{it} that realized immediately after the decision to withdraw.
Source: ECB SUCH (2016) and SPACE (2019) Data.

Information on incoming purchases. In the stylized model, I assumed that agents know the distribution of transaction sizes, but don't have any additional clue about the size of incoming payments when facing the withdrawal decision. As I have information on withdrawal choices and on the size of subsequent payments, I can provide evidence that is helpful to evaluate whether the above assumption is a legitimate one or not. In Figure 11, I focus on agents that decided to withdraw cash immediately before a certain transaction, of which I observe the size. I group transactions according to their sizes and compute the average withdrawal for each group of incoming transaction sizes. The Figure suggests quite strongly that individuals seem to anticipate their next payment, as the average withdrawal size rises as a function of the magnitude of the incoming transaction. How precisely do people know their next payment? This is not easy to say. In the quantitative model, I adopt a very flexible specification assuming that agents receive imperfect *signals* on the size of their next purchase, and I estimate the precision of those signals as a structural parameter.

4.2 The model

Consider the problem of an agent who has access to two types of payment instruments: cash and a cashless payment method (e.g., a debit card or a mobile payment app)[13]. The agent is infinitely lived. Time is discrete and indexed by t; each period represents an hour. At the start of every period, the agent may realize that she needs to purchase some good or service and receives a noisy signal about the size of the incoming transaction[14]. Depending on the size of the signal, or even if she did not receive any, the agent can decide to withdraw cash[15] from ATMs paying a fixed cost $b > 0$. Carrying around m units of cash entails a variable cost Rm per hour, independently of whether cash is spent for a purchase or just kept in the wallet. Settling a transaction with the cashless payment method entails a fixed cost κ (in this case potentially smaller than zero, i.e., a benefit), which is heterogeneous across individuals but constant through time. One should think of κ as a time-invariant taste for paying with cashless methods as opposed to paying with cash. Stores are of three types $\Phi \in \{c, d, cd\}$: stores of type c only accept cash payments, stores of type d only accept cashless payments (such as $d$ebit cards) and stores of type cd accept both. When entering a store of type d with cash on hand lower than the size of the purchase, agents fail to settle the transaction and face an utility cost increasing in the size of the lost purchase. Future periods are discounted at rate $\beta \in (0, 1)$.

Let m_t denote the amount of cash at the start of period t. Let j_t be an indicator for potential purchases: in particular, $j_t = 1$ if the agent needs to make a purchase in period t, and zero otherwise. Let $\tilde{s}_t$ denote the transaction size signal received in period t (missing when $j_t = 0$). Let w_t denote the amount of cash withdrawn in period t, and m'_t denote the amount of cash in the second phase of period t. Moreover, let s_t denote the actual size of the purchase in period t, and $\Phi_t \in \{c, d, cd\}$ the type of store visited. As in the analytical model, let p_t denote payment choices in period t and l_t denote lost purchases.

[13] In this paper, I don't deal with the issue of cashless adoption. As SUCH and SPACE data reveal that around 98% of people in SUCH and SPACE data have access to at least one cashless means of payment, understanding the determinants of adoption is not of first order importance to capture what drives payment choices in the Euro Area. If one is interested in a more general question such as establishing the conditions under which a cash-based society can become cashless, adoption is a relevant margin and should be taken into account. In a recently started project that will try to answer such questions (Moracci and Sorbera (2022)), we plan to endogenize cashless adoption to study its determinants in detail. For the purpose of the present paper, in the model I assume that every agent owns a cashless payment method and during the estimation I drop individuals that do not satisfy this requirement.

[14] To understand the role of signals, it is useful to think about them in the following way. Imagine that the agent realizes that she needs to buy a certain good, say a book. Despite she approximately knows the price of the book, she faces some uncertainty on the exact amount of money she will spend. Depending on how noisy the signal is, this uncertainty vanishes or becomes very sizeable.

[15] As I did for the two-period model, I do not allow for deposits. This is not a binding restriction in a model with no inflows of cash. However, in SUCH and SPACE data I observe that many people obtain cash from other sources with respect to ATMs (cash income and cash transfers from family and friends, for instance). The model is not appropriate to describe the payment and cash management behavior of these people, which I therefore drop in my estimation procedure.

FIGURE 12: Timing of the quantitative model.

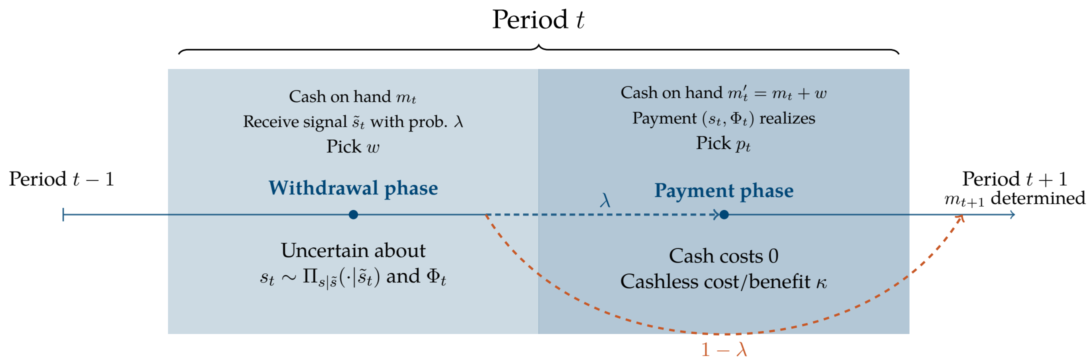


Figure 12 illustrates the timing of the model. Agents, each of them endowed with a time-invariant type κ, enter each period observing the value of cash holdings m_t. In some periods, they need to purchase something; in other periods, they don't: the need to purchase something in each period j_t is randomly drawn from a Bernoulli distribution with parameter λ, i.e., $j \sim Ber(\lambda)$. If they need to purchase something (i.e., if $j_t = 1$), they receive a signal $\tilde{s}_t$ drawn from a distribution $\tilde{F}(\cdot)$. Based on their type κ, on m_t and $\tilde{s}_t$ (if they received one) agents decide whether to pay the fixed cost b and withdraw a positive amount of cash w_t. They can also decide to withdraw cash in periods where they don't need to purchase anything. Depending on the withdrawal choice, the level of cash holdings in the second subperiod is determined by $m_t' = m_t + w_t$. Afterwards, if $j_t = 1$ the agents enter the payment phase of period t; otherwise, they move to period $t+1$. After entering the payment phase, s_t and Φ_t realize. In particular, s_t is drawn from a conditional distribution $\Pi_{s|\tilde{s}}(\cdot|\tilde{s})$ such that $\mathbb{E}(s|\tilde{s}) = \tilde{s}$. When they face a non-trivial payment choice (i.e., if they entered a shop that accepts both payment methods and if they have sufficient cash on hand) need to decide whether to pay with cards ($p_t = 1$) or with cash. This last decision pins down the level of initial cash holdings in period $t+1$. If at time t the agent does not need to buy anything (i.e., if $j_t = 0$), she still can decide whether to withdraw cash or not. After this decision, the agent will move to the period $t+1$.

Agents have to solve a infinite horizon, dynamic stochastic cost minimization problem given by

$$
\begin{aligned}
\min_{\{w_t,p_t\}_{t=0}^{\infty}} \quad & \mathbb{E}_{\{s_t,\Phi_t\}_{t=1}^{\infty}} \left[\sum_{t=0}^{\infty} \beta^t \left(R m_t' + b \mathbb{1}_{\{w_t>0\}} + \kappa \mathbb{1}_{\{p_t=1\}} + u(s_t) \mathbb{1}_{\{l_t=1\}} \right) \middle| m_0 \right] \\
\text{subject to} \quad & m_t' = m_t + w_t, \\
& m_{t+1} = m_t' - s_t j_t (1-p_t)(1-l_t), \\
& (m_t - s_t)(1-p_t) \mathbb{1}_{\Phi_t \in \{d,cd\}} \geq 0, \\
& (m_t - s_t)(1-l_t) \mathbb{1}_{\Phi_t = c} \geq 0, \quad \forall t,
\end{aligned}
\tag{11}
$$

where the objective and constraints have a similar structure with respect to the two-period model presented in the previous Section.

I now rewrite problem (11) in a simpler and more intuitive dynamic programming notation. Consider the problem for an agent of type κ. Let $E\widehat{V}(m,\kappa)$ denote the value of the problem at the start of the period *before* the realization of j, i.e., before knowing whether the agent will face a transaction or not in this period. The value $EV(m,\kappa)$ is given by

$$E\widetilde{V}(m,\kappa) = \lambda \int_0^{+\infty} \widetilde{V}(m,\tilde{s},\kappa) d\tilde{F}(\tilde{s}) + (1-\lambda)\left(Rm + \beta E\widetilde{V}(m,\kappa)\right), \tag{12}$$

where λ (the probability of facing a transaction) multiplies $E\tilde{V}(m,\tilde{s},\kappa)$, i.e., the value of the problem for an agent that faces a transaction in the current period and receives a transaction size signal $\tilde{s}$, whereas $(1-\lambda)$ (the probability of facing no transactions) multiplies the value of the problem for an agent that doesn't need to make any purchase in this period. Notice that agents which are not facing any purchase will never withdraw cash for future periods. Indeed, there is no point in withdrawing more cash now if they are not going to use it with certainty, given that they can still withdraw in the next period in case a payment signal arrives. The value of the problem for an agent of type κ who received a transaction size signal $\tilde{s}$ is instead given by

$$\widetilde{V}(m,\tilde{s},\kappa) = \min\left\{ b + \arg\min_{w\geq 0} EV(m+w,\tilde{s},\kappa), EV(m,\tilde{s},\kappa) \right\}, \tag{13}$$

where $EV(m,\tilde{s},\kappa)$ is the expected value of the problem in the payment phase for an agent of type κ, with m units of cash on hand and a transaction size signal $\tilde{s}$. The latter is given by

$$EV(m,\tilde{s},\kappa) = \int_0^{\infty} V(m,s,\kappa)\pi(s|\tilde{s})\mathrm{d}s, \tag{14}$$

where $\pi(s|\tilde{s})$ is the conditional probability that the payment size is equal to s when the signal is given by $\tilde{s}$, and the value at payment is

$$V(m,s,\kappa) = Rm + \phi^c(s)V^c(m,s,\kappa) + \phi^d(s)V^d(m,s,\kappa) + \phi^{cd}(s)V^{cd}(m,s,\kappa), \tag{15}$$

where $\phi^h(s) = \Pr(\Phi = h|\, s)$ (so that $\phi^c(s)+\phi^d(s)+\phi^{cd}(s) = 1$ for any s) and $V^h(m,s,\kappa)$ for $h \in \{c,d,cd\}$ respectively denote the value of facing a payment of size s for an agent of type κ with cash on hand m visiting a shop of type h. For shops that only accept cash, the value is given by

$$V^c(m,s,\kappa) = \begin{cases} \beta \cdot E\widetilde{V}(m-s,\kappa) & \text{if } m \geq s, \\ u(s) + \beta \cdot E\widetilde{V}(m,\kappa) & \text{if } m < s. \end{cases}$$

For shops that only accept cashless payments, the value is given by

$$V^d(m, s, \kappa) = \kappa + \beta \cdot E\widetilde{V}(m, \kappa).$$

Finally, for shops that accept both types of payment, the value is given by

$$V^{cd}(m, s, \kappa) = \begin{cases} \min\left\{\beta \cdot E\widetilde{V}(m-s, \kappa), \kappa + \beta \cdot E\widetilde{V}(m, \kappa)\right\} & \text{if } m \geq s, \\ \kappa + \beta \cdot E\widetilde{V}(m, \kappa) & \text{if } m < s. \end{cases}$$

4.3 Functional forms and numerical solution

Some functional forms must be chosen in order to be able to solve the model numerically. First, I assume that the taste for cashless/cash payments is normally distributed, i.e., that $\kappa \sim N(\mu_\kappa, \sigma_\kappa)$. Second, I need to specify the distribution $\tilde{F}$ of transaction size signals $\tilde{s}$ and the conditional probability distribution Π of transaction sizes given observed signals. I assume a lognormal distribution for transaction size signals, i.e., $\tilde{s} \sim LN(\mu_{\tilde{s}}, \sigma^2_{\tilde{s}})$. I also assume that the actual transaction size s is given by

$$s = \tilde{s} \cdot \varepsilon,$$

where $\varepsilon \sim LN(\mu_\varepsilon, \sigma^2_\varepsilon)$ is a surprise component. Since the product of log-normal distributions is again log-normal, I will have that $s \sim LN(\mu_s, \sigma^2_s)$, an assumption that fits the data on transaction sizes pretty well, as I argue in Appendix C.1. After picking μ_s and σ^2_s (that can be elicited from the data on actual transactions) and under the assumption that signals are on average correct ($\mathbb{E}(\varepsilon) = 1$), it is possible to back up the parameters $\mu_{\tilde{s}}$ and $\sigma_{\tilde{s}}$ for any given level of relative noise $\overline{\sigma}_\varepsilon = \sigma_\varepsilon/\sigma_s \in [0, 1]$. In Appendix C.2 I describe in detail all the derivations and I show how the conditional distribution $\Pi(s|\tilde{s})$ changes as the precision of signals improves or worsens. An implication of this modelling choice is that the variance of the conditional distribution of s given $\tilde{s}$ is increasing in the latter: people face more uncertainty on the size of large purchases than over the size of small ones[16]. As the Appendix clarifies, this specification is quite general and it embeds the extreme cases of perfect information on the size of the next payment at the time of a withdrawal ($\overline{\sigma}_\varepsilon = 0$, as in Briglevics and Schuh (2021)) and of no information at all on top of knowing the unconditional distribution of payments ($\overline{\sigma}_\varepsilon = 1$, as the analytical two-period model presented in the previous Section). Allowing for such a general information structure is important in order to avoid to contaminate the estimation results with restrictive assumptions. The extent to which agents are able to anticipate incoming payments is an important driver of choices: less precise information induces extra precautionary motives for holding cash, as agents cannot observe

[16] A real-life example is again helpful. Think about two agents: one needs to buy a coffee, the other needs to buy a fridge. It makes sense that the second one faces higher uncertainty on the exact size of the transaction.

exactly the size of the next payment when deciding how much to withdraw. Therefore, the presence and informational content of transaction size signals must be structurally estimated rather than imposed *apriori*. Third and last, I need to choose the functional form for $u(s)$, the disutility from lost purchases as a function of the size of the purchase the agent was not able to carry out. An intuitive requirement of such function is that $u'(s) > 0$, i.e., it is worse to lose a small purchase than a small one. The specification I adopt is $u(s) = \alpha s$, with $\alpha > 0$.

I solve the model numerically using value function iteration on discretized grids for m, $\tilde{s}$, s and κ. For m, $\tilde{s}$ and s I choose unequally spaced grids to improve precision at small values. For any given transaction size distribution F, I pick the 99th percentile of F as upper bound of the grid for $m, \tilde{s}$ and s, in order to focus on the relevant portion of the state space. As a lower bound for s and $\tilde{s}$, I pick 0.01 as there cannot be a payment smaller than EUR 0.01. As a lower bound for m, I clearly pick 0. Numerically solving the model yields three policy functions: a policy function for optimal withdrawals before a payment $w(m, \tilde{s}, \kappa)$, one for optimal withdrawals in periods with no payments $w(m, \kappa)$ and finally one for optimal payment choices (when both options are available) $p(m, s, \kappa)$.

4.4 Estimation strategy

The model is estimated for each Euro Area country using 2019 data from the SPACE survey. As specified above, I restrict the estimation sample to people that i) have access to at least a cashless payment method, and ii) do not receive income in cash regularly.

Some parameters of the model can be directly calibrated using SPACE data. For instance, the two parameters of the log-normal transaction size distribution F (μ_s and σ_s) can be easily calibrated for each country to match the mean and standard deviation of $\log(s)$. I can also calibrate the probabilities $\phi^h(s)$ of each merchant acceptance regime $h \in \{c, d, cd\}$ as a function of the size of the transaction. Letting $\phi^h(s)$ be a function of s is important as the data clearly reveals that acceptance probabilities depend on the size of the transaction, as merchants are more likely to accept cashless methods for larger payments than for small ones (or, more precisely, merchants that sell low-value goods are less likely to accept cashless payments with respect to stores that sell highly-priced goods and services). I calibrate probabilities $\phi^h(s)$ for each country by estimating a logit where I let probabilities of merchant acceptance regimes be a quadratic function of s; this procedure yields a set of 6 coefficients $(\beta_0^c, \beta_1^c, \beta_2^c, \beta_0^d, \beta_1^d, \beta_2^d)$. Additional details are provided in Appendix C.3. After the calibration stage, for any country i I have a set of calibrated parameters

$$\mathbf{\Gamma}_i = \left(\mu_{si}, \sigma_{si}, \beta_{0i}^c, \beta_{1i}^c, \beta_{2i}^c, \beta_{0i}^d, \beta_{1i}^d, \beta_{2i}^d\right).$$

For every country, I have to structurally estimate the set of remaining parameters

$$\mathbf{\Theta} = (\beta, R, b, \mu_\kappa, \sigma_\kappa, \overline{\sigma}_\varepsilon, \alpha, \lambda)\,.$$

This set of parameters include: the discount factor $\beta \in (0,1)$, the opportunity cost of holding one unit of cash (one EUR) $R > 0$, the withdrawal cost $b > 0$, the mean μ_κ and standard deviation $\sigma_\kappa > 0$ of the the distribution of tastes for cashless payments, the relative noise of signals $\overline{\sigma}_\varepsilon \in [0,1]$, the disutility per EUR of losing a purchase $\alpha > 0$ and the probability of receiving a transaction size signal $\lambda > 0$. Notice that I cannot simply calibrate λ to match the number of payments as in the data I observe only *completed* transactions and not the ones that did not occur because of a lost purchase episode. Therefore, λ must be structurally estimated as well.

The estimation exploits the method of simulated moments. Note that, taking the set of calibrated parameters $\mathbf{\Gamma}$ as given, I can solve the model for any set of parameters $\mathbf{\Theta}$ and get the implied policy functions. I can then simulate payment and cash management paths for a synthetic sample of individuals. In particular, I simulate a panel dataset that replicates all salient feature of SPACE data: after drawing a series of shocks (timing of purchases, size of transaction signals and actual purchases) I generate a longitudinal dataset in which I follow N agents for D days, and I assume that the Dth day is the one in which agents compile their payment diaries. I store the information relevant to create a synthetic version of SPACE data for the diary day: the time path of cash holdings, the size of each purchase, payment choices, payment acceptance policies of visited merchants, and the timing and size of each withdrawal. I also impose in the simulated data the censoring structure of SPACE, to minimize differences: for instance, the number of reported payments in the diary day is capped at 8. I set the number D high enough that the arbitrary initial conditions m_{0i} do not play any role. A reasonable value is $D = 7$ (I simulate the data for a week and keep the last day of the week as the payment diary day), as I show using simulations in Appendix C.4.

My goal is to minimize some weighted distance between selected moments from SPACE data and moments computed on the synthetic sample obtained from simulating the structural model. For any $\theta \in \mathbf{\Theta}$, my criterion function takes the form

$$\Lambda(\theta) = \left[\mu^d - \mu(\theta)\right]' W^{-1} \left[\mu^d - \mu(\theta)\right],$$

where μ^d is a vector of moments computed on the osberved data, $\mu(\theta)$ is an average vector of moments computed on S simulated datasets after solving the model for the parameter vector θ, and W is a weighting matrix. In particular, I compute $\mu(\theta)$ by repeating the simulation S times for fixed θ and getting

$$\mu(\theta) = \frac{1}{S}\sum_{s=1}^{S} \mu_s(\theta, \epsilon_s),$$

where ϵ_s represents the vector of realized shocks in the sth simulation. Averaging over S simulations reduces the effect of random draws influencing agents' choices (Eisenhauer, Heckman, and Mosso (2015)). I choose $S = 10$, a choice I extensively discuss how in Appendix C.5, where I show how the distance function evaluated at the optimum changes for various levels of S. As a weighting matrix, again following Eisenhauer, Heckman, and Mosso (2015), I pick a matrix with the variances of the empirical moments (simulated using bootstrap by resampling the original data with replacement 100 times) on the diagonal and zero otherwise. Therefore, I can rewrite my problem as the nonlinear least-squares problem

$$\hat{\theta} = \arg\min_{\theta} \sum_{k=1}^{K} \left(\frac{\mu_k^d - \mu_k^t(\theta)}{\sigma_k^d} \right)^2, \tag{16}$$

where K is the number of moments employed in the estimation.

4.4.1 Identification (*In progress*)

To estimate θ, I rely on a set of moments related both to cash management and to payment choices. First, following the literature on cash management (Alvarez and Lippi (2013), Alvarez and Lippi (2017)) I pick the four most relevant statistics concerning this dimension of household behavior, namely: the average level of cash holdings M, the average withdrawal size W, the average amount of cash on hand at the time of a withdrawal $\overline{M}$ and the average number of cash withdrawals in a given day n_W (a proxy for the frequency of withdrawals). Second, I pick the following four moments related to payment behavior: the share C of cashless payments when both options are possible, the average cash payment s_c, the average cashless payment s_d and the average number of payments in a given day n_P. The choice of moments is motivated by the urge to capture both features of payment choices and cash management policies by households. There are no theoretical results that guarantee identification using the method of simulated moments in this kind of setting. However, the moments are chosen in such a way that each one of them is informative on some (or multiple) parameters and such that each parameter shifts at least one moment.

Clearly, the opportunity cost of cash R is likely to affect negatively both average cash holdings M and the average withdrawal W. An increase in the withdrawal cost b should affect W positively, while decreasing $\overline{M}$ and the frequency of withdrawals n_W - when going to ATMs is more expensive, agents do that less often and withdraw more. Notice that an increase in b will also have a positive impact on the share of voluntary cashless payments C, as derived theoretically in the two-period model. Also μ_κ and σ_κ affect C, which does not depend only on the mean value of κ but on the entire distribution; clearly, these parameters also shift cash management moments, as people that prefer cards will hold less cash and withdraw less often. Turning to the relative level of noise in transaction size signals, it affects several moments: first, as more detailed information on incoming payments decrease the precautionary motive for holding cash and for using cards when $\kappa > 0$, both M, $\overline{M}$ and C will be positively affected by an increase in $\overline{\sigma}_{\varepsilon}$. The utility loss α for each EUR of lost purchases affect both these moments and n_P: when α rises and missing a purchase hurts a lot, agents will adopt strategies in order to avoid this outcome, and the number of payments will tend to the one that would prevail with signals coming at rate λ in the absence of imperfect cashless acceptance.

To insure convergence to a global minimum of the criterion function and avoid getting stuck in local minima, I exploit a controlled random search algorithm with local mutation (`NLOpt.jl` package). After imposing lower and upper bounds on each parameter, and adjusting the bounds whenever they are binding at the candidate solution, the controlled random search algorithm samples a population of starting points within all bounds, and evolve them by throwing away, for each step, the worst point in the population and replacing with promising newly found ones. As the algorithm searches extensively in the feasible space of parameters, it avoids dependence on initial guesses and it deals with the concern of local minima. After a thorough global search in the parameter space using CRS, I select the best candidate and use it as the intial guess in a local optimization procedure aimed at refining the optimal value.

5 Estimation results: explaining cross-country differences (In progress)

In this Section[17], I first provide evidence on the extent of cross-country heterogeneity in cash management and payment behavior in the Euro Area. Secondly, I present the estimation results and evaluate the model's ability to replicate observed features of the data.

5.1 Payment and cash management behavior in the Euro Area

Before presenting the estimation results, I provide evidence showing what is the extent of heterogeneity in payment and cash management behavior in the Euro Area. In Table 3 I display the eight moments on cash management and payment choices that I use in the estimation procedure, computed for all countries using the most recent SPACE data for 2019.

As the Table shows, there is sizable heterogeneity across the Euro Area along all these dimensions. Average cash balances held by consumers range from around 30-40 euros (as in Portugal and France) to more than 60 euros (as in Austria or Italy). In some

[17] The results I show in this Section are preliminary: I'm currently working on i) improving the fit, ii) obtain standard errors for estimated parameters, and iii) estimate the model using more recent data from the 2022 wave of SPACE.

TABLE 3: Cash management and payment choices, cross-country evidence.

Country	M	$\overline{M}$	W	n_w	C	s_c	s_d	n_P
Austria	76.0	14.0	80.0	0.17	0.21	17.0	39.0	2.2
Belgium	56.0	18.0	67.0	0.15	0.39	15.0	35.0	2.1
Estonia	35.0	7.8	43.0	0.084	0.48	12.0	20.0	1.9
Finland	42.0	9.7	57.0	0.074	0.57	15.0	25.0	2.1
France	42.0	9.0	51.0	0.16	0.28	11.0	39.0	2.1
Greece	57.0	20.0	55.0	0.15	0.22	13.0	31.0	2.5
Ireland	55.0	11.0	72.0	0.17	0.25	15.0	32.0	2.4
Italy	61.0	14.0	70.0	0.14	0.23	13.0	37.0	2.4
Latvia	34.0	8.5	42.0	0.13	0.38	8.6	15.0	2.5
Lithuania	43.0	11.0	45.0	0.12	0.36	12.0	17.0	2.2
Luxembourg	98.0	21.0	100.0	0.11	0.44	20.0	59.0	2.4
Portugal	30.0	9.4	33.0	0.24	0.19	7.8	26.0	2.5
Slovakia	43.0	9.7	45.0	0.18	0.34	10.0	19.0	2.2
Slovenia	49.0	14.0	55.0	0.17	0.26	13.0	25.0	2.1
Spain	48.0	15.0	51.0	0.14	0.16	11.0	29.0	2.3
Euro Area	51.0	13.0	58.0	0.14	0.3	13.0	29.0	2.2

Note: The first four moments concern cash management: M are average cash holdings (EUR), W is the average withdrawal size, $\overline{M}$ is the average cash balance at the time of a withdrawal, and n_W is the average number of withdrawals per day. The last four moments concern payment choices: C is the share of cashless payments when both options are available, s_c is the average size of transactions settled with cash, s_d is the average size of transactions settled with cards, and n_P is the average number of transactions per day. *Source: SPACE (2019) Data.*

countries, including Austria, Ireland and Italy, the average withdrawal is higher than 70 euros; people from Latvia, Lithuania and especially Portugal, instead, withdraw relatively little cash, with average withdrawals around 30-40 euros. The average Italian or Greek consumers go to withdraw money at an ATM when they still have 15 to 20 euros on hand; in France and Portugal, consumers visit ATMs when they have approximately 9 euros left (one third of their median balances). The same patterns arise for the share of payments settled using cards when having both options available C: in Finland, almost 60% of such payments are settled using cards; in Greece, Italy, Portugal and Spain this share is close to 20%. In some countries, there is a huge gap between the average cash payment and the average cashless one: among others, this applies to Greece, Ireland and Italy, but also France. In other countries, such as Estonia and Lithuania, the difference is much smaller. Merchant acceptance of payment methods is highly heterogeneous as well, as seen in Figure 10: it ranges from almost perfect (as in Finland) to very imperfect (as in Austria, Italy, Portugal and Slovakia).

Table 4: Estimated parameter values $\hat{\theta}$ for all countries.

Country	β	R	b	μ_κ	σ_κ	$\overline{\sigma}_\varepsilon$	α	λ
Austria	0.999	0.000256	9.8	3.02	4.33	0.993	0.098	0.0992
Belgium	0.999	0.0004	7.53	0.235	4.92	0.998	0.0997	0.0953
Estonia	0.991	9.68e-5	6.44	-0.0931	4.97	0.00505	0.00848	0.0808
Finland	0.994	0.000103	6.52	-0.287	3.88	0.0394	0.00246	0.0883
France	0.99	0.000609	5.47	2.07	5.21	0.967	0.0968	0.0848
Greece	0.998	0.000654	8.23	2.41	4.62	0.0695	0.0862	0.096
Ireland	0.99	0.000405	9.39	2.16	4.92	0.188	0.0961	0.0785
Italy	0.99	7.13e-6	9.6	2.19	4.99	0.879	0.0932	0.0995
Latvia	0.999	0.000282	6.32	0.0751	5.06	0.000578	0.0894	0.0852
Lithuania	0.999	0.000434	5.6	0.0252	4.97	0.0527	0.093	0.0948
Luxembourg	0.992	0.000517	10.1	-0.0266	4.87	0.0132	0.0927	0.0998
Portugal	0.992	0.000225	5.45	0.0636	4.66	0.000975	0.00662	0.099
Slovakia	0.996	6.69e-6	6.26	0.333	4.91	0.00837	0.0755	0.0753
Slovenia	0.99	0.000287	3.33	1.02	3.21	0.932	0.0996	0.0894
Spain	0.999	0.000414	8.75	2.81	4.07	0.928	0.0994	0.0994

5.2 Estimation results

In Table 4 I display the estimation results. Bear in mind that this results are *preliminary*: as I'm still working to improve the estimation routine and the identification strategy (i.e., the choice of moments) the reported figures could change in future versions of this work. Despite this, I believe that the results obtained are still quite informative. The main take-away is that differences in merchant acceptance of payment method only explain a portion of cross-country heterogeneity. Even accounting for different acceptance profiles across countries, as I did in the calibration procedure, substantial variation in structural parameters is needed to replicate observed differences in behavior across countries.

Of course, the estimated discount factors β are extremely high, as a consequence of the fact that period length is one hour in the model. This is also the reason why the estimated opportunity cost of holding cash R (which has to be paid in every period) is so small. Even though R is tiny, results reveal that it is highly heterogeneous across countries, with huge differences between the cost of holding cash for a French consumer and for an Italian one. There is much less variation in withdrawal costs, for which the point estimates are roughly consistent with results from Briglevics and Schuh (2021). Estimation results for μ_κ and σ_κ point towards the existence of sizeable within-country heterogeneity in tastes for using cashless methods. In most countries, the average person prefers to use cash, with some exceptions (Estonia, Finland, Luxembourg). The estimation reveals huge variation in $\overline{\sigma}_\varepsilon$: even though the extent to which consumers

Table 5: Simulated moments μ^s for estimated parameter values $\hat{\theta}$.

Country	M	$\overline{M}$	W	n_w	C	s_c	s_d	n_P
Austria	75.82	18.68	89.37	0.184	0.2077	16.52	37.87	2.228
Belgium	54.2	13.62	102.3	0.08623	0.3559	14.31	34.69	2.126
Estonia	33.92	9.948	85.83	0.1048	0.4683	13.09	20.96	1.855
Finland	43.85	10.38	107.8	0.08408	0.5016	15.77	26.94	2.068
France	39.39	9.688	76.29	0.156	0.3078	11.79	36.83	1.994
Greece	52.01	14.59	119.1	0.1682	0.2227	14.78	27.64	2.235
Ireland	52.16	12.46	84.65	0.1557	0.2585	14.73	30.16	2.278
Italy	60.8	12.97	111.2	0.1501	0.2556	13.49	33.19	2.282
Latvia	34.5	11.31	50.93	0.1146	0.3936	8.428	15.77	2.223
Lithuania	40.11	15.99	63.88	0.1419	0.3697	12.13	19.14	2.101
Luxembourg	93.42	9.717	139.0	0.1109	0.4238	22.26	59.59	2.312
Portugal	29.67	8.035	46.66	0.1324	0.2314	7.784	18.41	2.142
Slovakia	43.08	13.29	62.95	0.1338	0.325	9.989	21.6	2.161
Slovenia	51.11	13.19	57.65	0.1619	0.2636	12.38	27.04	2.039
Spain	48.86	12.31	70.53	0.1519	0.1557	9.989	27.32	2.28

know the size of their incoming purchases could change across countries, it looks like the range of estimates for this parameter is too wide, a result that urges for further work on the estimation strategy. The same applies to α, for which the estimated results for countries such as Finland and those for countries like Austria seem incompatible in terms of magnitude. Finally, the estimated values of λ look reasonable.

5.3 Model fit

Even though the some of the estimated parameters look off, the estimated model is reproducing payment and cash management behavior in most countries quite well, as a comparison of Table 5 and Table 4 shows. The main problem with the fit, as of now, seems the tendency of estimated model across all countries to *overshoot* the average withdrawal size with respect to that observed in the data. The fact that errors in matching W are always of the same sign deserves further investigation, and I hope to be able to address this problem in the next version of this paper. On all the other moments, the estimated models for each country seem to perform relatively well, although the fit is still not good enough to allow for additional analyses.

5.4 Next steps and future research

I am currently working on improving the estimation procedure and understand what generates somewhat implausible estimates for some of the parameters and prevents the estimated model to match average withdrawals W. Understanding the source of such issues could increase confidence in results, and improving the model fit could allow additional analyses: a priority would be to quantify the relative contribution of variation in each structural parameters, and that of differences in merchant acceptance, in generating the observed heterogeneity in behavior across countries. Moreover, the estimated model could be used for i) estimating the value of having access to a cashless method in each country; ii) evaluating the effects of changes such as increases in cashless acceptance.

In this paper, I adopt a partial equilibrium approach, focusing on buyers' decisions and taking merchant acceptance levels as given. While this creates no problem for descriptive analysis (for instance, to understand the sources of regional heterogeneity), it is harder to use this framework to study the effect of policy changes. While it is possible to study the first-order effects of an increase in cashless acceptance moreover, the estimated effects will not take into account that merchants themselves may react to changes in cash management and payment choices by consumers, increasing acceptance even more. Moreover, as the problem of merchants is not explicitly modeled, the model isn't useful if one wants to understand how to *generate* a rise in cashless acceptance, nor it is capable of addressing relevant policy questions. *To increase the share of cashless payments, is it more efficient to subsidize consumers who use cards or merchants who accept them? What are the welfare effects of measures such as limits to cash usage or fines to merchants that do not accept cashless methods?* To answer such questions reliably, one needs to endogenize merchant choices and adopt a general equilibrium approach. In recently started work (Moracci and Sorbera (2022)), we try to fill such gap by building an extension of the model presented here that embeds strategic interaction among merchants who have to decide which payment methods to accept.

6 Conclusion

High-quality, transaction level data on payment method decisions of Euro Area consumers shows a novel fact on payment behavior: when cashless acceptance is imperfect, individuals often use cashless methods even if they have sufficient cash on hand to carry out a purchase, in order to preserve cash for future shopping trips where cards might not be accepted. I present a novel analytical model that rationalizes such finding and yields predictions on the interaction between payment choices, cash management and levels of cashless acceptance by merchants. The model generalizes results of existing studies and rationalizes features of behavior that previous theories could not capture, by providing a key insight: cashless payments can act as a *cash management tool*, as long as they are cheaper than withdrawals. I then present a quantitative model that builds on the analytical one and estimate it across Euro Area countries. Preliminary results, that deserve further investigation, seem to suggest that cross-country differences in payment and cash management behavior are not only a consequence of different levels of merchant acceptance, but arise as a consequence of regional variation in environmental factors such as the cost of holding cash and preferences for cashless versus cash payments.

References

Abramova, Svetlana et al. (2022). "What Can CBDC Designers Learn from Asking Potential Users? Results from a Survey of Austrian Residents". In: (cit. on p. 1).

Alvarez, Fernando and Lippi, Francesco (2013). "The Demand of Liquid Assets with Uncertain Lumpy Expenditures". In: *Journal of Monetary Economics* 60.7, pp. 753–770. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2013.05.008 (cit. on p. 34).

– (2017). "Cash Burns: An Inventory Model with a Cash-Credit Choice". In: *Journal of Monetary Economics* 90, pp. 99–112. DOI: 10.1016/j.jmoneco.2017.07.001 (cit. on pp. 2, 4, 7, 9, 10, 13, 23, 24, 34, 46, 47).

Alvarez, Fernando, Lippi, Francesco, and Robatto, Roberto (Apr. 2019). "Cost of Inflation in Inventory Theoretical Models". In: *Review of Economic Dynamics* 32, pp. 206–226. ISSN: 10942025. DOI: 10.1016/j.red.2018.11.001 (cit. on p. 1).

Arango, Carlos, Huynh, Kim P., Fung, Ben, et al. (2012). "How Do You Pay? The Role of Incentives at the Point-of-Sale". In: *Bank of Canada Review* (Autumn), pp. 31–40 (cit. on p. 3).

Arango, Carlos, Huynh, Kim P., and Sabetti, Leonard (2015). "Consumer Payment Choice: Merchant Card Acceptance versus Pricing Incentives". In: *Journal of Banking and Finance* 55.February 2015, pp. 130–141. ISSN: 03784266. DOI: 10.1016/j.jbankfin.2015.02.005 (cit. on p. 3).

Arango, Carlos A., Bouhdaoui, Yassine, et al. (2014). "Cash Management and Payment Choices: A Simulation Model with International Comparisons". In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.2378840 (cit. on p. 47).

Bagnall, John et al. (2016). "Consumer Cash Usage: A Cross-Country Comparison with Payment Diary Survey Data$_*$". In: *International Journal of Central Banking* 12.4, pp. 1–61. ISSN: 18157556. DOI: 10.2139/ssrn.2446786 (cit. on pp. 3, 7, 49).

Baumol, William J. (1952). "The Transactions Demand for Cash: An Inventory Theoretic Approach". In: *The Quarterly Journal of Economics* 66.4, p. 545. ISSN: 00335533. DOI: 10.2307/1882104 (cit. on p. 3).

Boeschoten, Willem C. (1992). *Currency Use and Payment Patterns*. ISBN: 0-7923-1710-6. DOI: 10.1007/978-94-011-2518-5 (cit. on p. 53).

Bouhdaoui, Yassine and Bounie, David (2012). "Modeling the Share of Cash Payments in the Economy: An Application to France". In: *International Journal of Central Banking* 8.4, pp. 175–195. ISSN: 18154654. DOI: 10.2139/ssrn.2132449 (cit. on p. 3).

Briglevics, Tamas and Schuh, Scott (2021). "This Is What's in Your Wallet... And How You Use It". In: *SSRN Electronic Journal* 14. DOI: 10.2139/ssrn.2431322 (cit. on pp. 4, 6, 26, 31, 37, 56).

ECB (2020). "Study on the Payment Attitudes of Consumers in the Euro Area (SPACE)". In: December (cit. on p. 6).

Eisenhauer, Philipp, Heckman, James J., and Mosso, Stefano (May 2015). "ESTIMATION OF DYNAMIC DISCRETE CHOICE MODELS BY MAXIMUM LIKELIHOOD AND THE SIMULATED METHOD OF MOMENTS: ESTIMATION OF DYNAMIC MODELS". In: *International Economic Review* 56.2, pp. 331–357. ISSN: 00206598. DOI: 10.1111/iere.12107 (cit. on pp. 34, 59).

Esselink, Henk and Hernández, Lola (2017). "The Use of Cash by Households in the Euro Area". In: *Occasional Paper Series* 201. DOI: 10.2866/377081 (cit. on p. 6).

Huynh, Kim P., Schmidt-Dengler, Philipp, and Stix, Helmut (2014). "The Role of Card Acceptance in the Transaction Demand for Money". In: *Oesterreichische Nationalbank Working Papers* 49.196, pp. 1–40 (cit. on pp. 3, 7).

Klee, Elizabeth (2008). "How People Pay: Evidence from Grocery Store Data". In: *Journal of Monetary Economics* 55.3, pp. 526–541. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2008.01.009 (cit. on pp. 2, 3, 6, 7).

Moracci, Elia and Sorbera, Silvio (2022). "Payment Choices and Cash Management with Endogenous Merchant Acceptance" (cit. on pp. 11, 28, 39).

Rogoff, Kenneth S (2017). *The Curse of Cash* (cit. on p. 1).

Tobin, James (1956). "The Interest-Elasticity of Transactions Demand For Cash". In: *The Review of Economics and Statistics* (cit. on p. 3).

Wakamori, Naoki and Welte, Angelika (2017). "Why Do Shoppers Use Cash? Evidence from Shopping Diary Data". In: *Journal of Money, Credit and Banking* 49.1, pp. 115–169. ISSN: 15384616. DOI: 10.1111/jmcb.12379 (cit. on p. 6).

Wang, Zhu and Wolman, Alexander L. (2016). "Payment Choice and Currency Use: Insights from Two Billion Retail Transactions". In: *Journal of Monetary Economics* 84, pp. 94–115. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2016.10.005 (cit. on pp. 3, 7, 49).

Whitesell, William C. (1989). "The Demand for Currency versus Debitable Accounts: Note". In: *Journal of Money, Credit and Banking* 21.2, p. 246. ISSN: 00222879. DOI: 10.2307/1992373 (cit. on pp. 2–4, 7, 9, 13, 23, 46, 47).

A Empirical appendix

A.1 Data cleaning and payment choice sets

The raw version of the data made available by the ECB has a major shortcoming: participants are not asked to report the level of their cash holdings in the moments in which they perform transactions[18]. At a first glance, this lack of information may seem no big deal: given that agents reported their money balances at the start of the day, using the data on withdrawals and payments cash holdings should be straightforward to pin down at each point in time. Two issues arise nonetheless: first, a fraction of agents failed to report the timing of cash adjustments performed (in SPACE data no one did, as respondents were not asked); second, participants were not explicitly asked about possible cash deposits.

To minimize the loss of data related to these shortcomings, I adopted the following strategy. Concerning the first problem, I was able to recover the timing of cash replenishments for a share of the agents which failed to report it: using the fact that I can observe which payment method they employed in each transaction, I can pin down the timing of adjustments in all situations in which an adjustment is needed to explain a purchase (i.e., in which an agent purchased in cash a good worth more than her *unadjusted* cash holdings). The individuals for which the timing of replenishments couldn't be pinned down exactly were not excluded from the data, but the transactions for which the level of cash holdings was uncertain were dropped. The second issue can also be tackled exploiting the fact that agents reported their cash holdings at the end of the day. For all the agents for which we are able to track cash holdings, we can compute our predicted cash balances at the end of the day *assuming there were no deposits*. If the two figures differ, then an unreported deposit or replenishment must have taken place during the day, and we are therefore not sure that cash on end at time of each transaction is corresponding to the actual one. These observations were excluded as well, and so were the ones for which computed cash balances were negative at some point. Finally, all the observations for Malta and Cyprus were excluded as I found systematic differences between the reported cash at the end of the day and the one I computed [19]. The final sample I exploit for the analysis contains information on 176,593 transactions carried out by 100,471 individuals[20]. For a subsample I have access to a larger amount of information, since these participants also filled in the questionnaire. The variables I

[18] The absence of cash holdings could be due to the fact that previous literature (with some exceptions) did not stress their impact on payment decisions, focusing only on the size of the transaction. Further evidence about this is provided in the questionnaire, in which respondents were asked "*When shopping in shops, what is the amount below which you would typically pay with cash instead of other payment methods?*". This question implicitly assumes that payment decisions are monotonic in transaction sizes, thereby ignoring the impact of cash on hand on choices.

[19] This does not happen with other countries. Maybe a coding error in the data provided by ECB?

[20] A share of participants actually did not carry out any payment in the day of analysis. The subsample of actual payers is composed by 75,187 individuals.

have access to in the cleaned version of the data can be divided in three families. First, I have access to *demographic data* on all participants. Second, I can observe a substantial amount of *transaction-level data* for all transactions performed. Third, for a subsample of participants (which includes a fraction of agents interviewed in the SUCH survey and all agents interviewed in the SPACE survey), *questionnaire data* are also available.

A key aspect of the data is that it allows, for a large share of transactions, to perfectly observe the payment choice set of individuals, i.e., if they could use cash, cashless methods or both. First, tracking cash holdings at the moment of payments makes it possible to compare them with the associated transaction size and thereby to establish (for all 100,157 payments) if it was possible to carry out the transaction using cash: clearly, it is not possible to pay with cash if the transaction size is larger than current cash holdings. Formally, let m_{it} be cash holdings of individual i at time t and s_{it} be the transaction size she faces. Our dummy for the possibility to use cash $CashPoss_{it}$ is constructed by

$$CashPoss_{it} = \begin{cases} 1 & \text{if} \quad s_{it} \leq m_{it} \\ 0 & \text{if} \quad s_{it} > m_{it} \end{cases}$$

Second, combining information on card acceptance by merchants provided by respondents, payment methods employed and questionnaire answers, it has been possible to determine for a large share of payments if cashless payments were really an option for agents. There are two situations in which we are sure that cashless payments were an available option. The first situation, of course, is the one in which agents *did* use cashless methods to settle the transaction. The second situation is identified when two conditions are met: first, cashless payments must be accepted as a way to carry out the transaction (a condition I could check for all payments); second, the agent must have access to a payment card[21] (which I could check for a large fraction of payments[22]). Formally, let $CardOwn_i$ be a dummy equal to one if individual i owns a payment card (debit or credit) and to zero if she doesn't. Let $CashlessOwn_i$ be equal to one if individual i has access to at least a cashless payment method and equal to zero otherwise. Let $CashlessAcc_{it}$ be a dummy equal to one if for the payment faced at time t by individual i cashless payments are accepted. Let $Cash_{it}$ be a dummy equal to one if the payment method used by i at time t was effectively cash, and equal to zero otherwise. Our dummy for the possibility to use cashless methods $CashlessPoss_{it}$ is constructed

[21] Since I don't know exactly which payment methods are accepted at any given transaction, but I just know if any cashless payments are accepted, I assume that an agent *could* have made a cashless payment at a store in which cashless instruments are accepted *if and only if* he/she has access either to a debit or to a credit card or both. The reason behind this is that credit and debit cards are always accepted in stores that accept some cashless payment method, while (for instance) cheques are not. Thereby, saying that an agent which has access to cheques (or credit transfers) could have paid cashless at a store in which cashless methods are accepted would be very risky, while for agents that own either a credit or a debit card it seems reasonably safe.

[22] This are all the payments made by respondents to the questionnaire, for whom we have detailed information concerning access to cashless instruments, plus all the payments made by agents which performed at least a card payment.

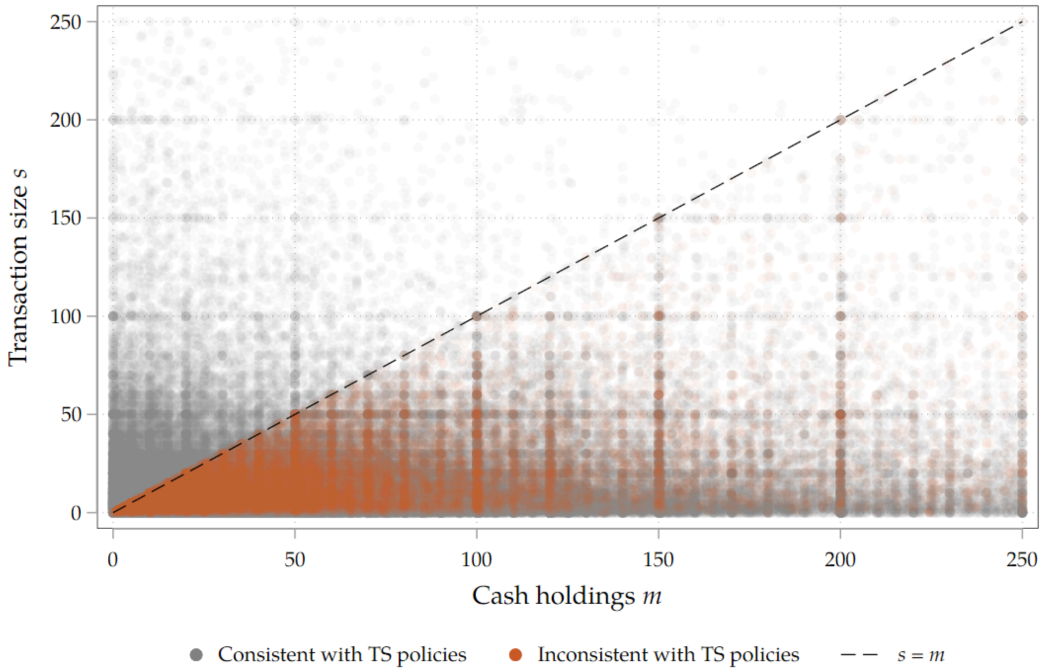
in the following way.

$$CashlessPoss_{it} = \begin{cases} 1 & \text{if} \quad Cash_{it} = 0 \vee \langle CardOwn_i = 1 \wedge CashlessAcc_{it} = 1 \rangle, \\ 0 & \text{if} \quad CashlessAcc_{it} = 0 \vee CashlessOwn_i = 0, \\ \cdot & \quad\quad \text{otherwise,} \end{cases}$$

where $\cdot$ represent a missing value. For these transactions I can exactly pin down the payment choice set of individuals, and I'm thereby able to distinguish between *forced* (only cash or only payment card available) and *voluntary* (both available) payment choices. Formally, let Vol_{it} be a dummy variable equal to one when both payment options (cash and cashless) were available for individual i at time t and to zero when only one was available, which is constructed in the following way.

$$Vol_{it} = \begin{cases} 1 & \text{if} \quad CashPos_{it} = 1 \wedge CashlessPos_{it} = 1 \\ 0 & \text{if} \quad CashPos_{it} = 0 \vee CashlessPos_{it} = 0 \\ \cdot & \text{if} \quad CashlessPos_{it} = \cdot \end{cases}$$

FIGURE 13: Whitesell (1989)'s transaction-size threshold policies and the data.



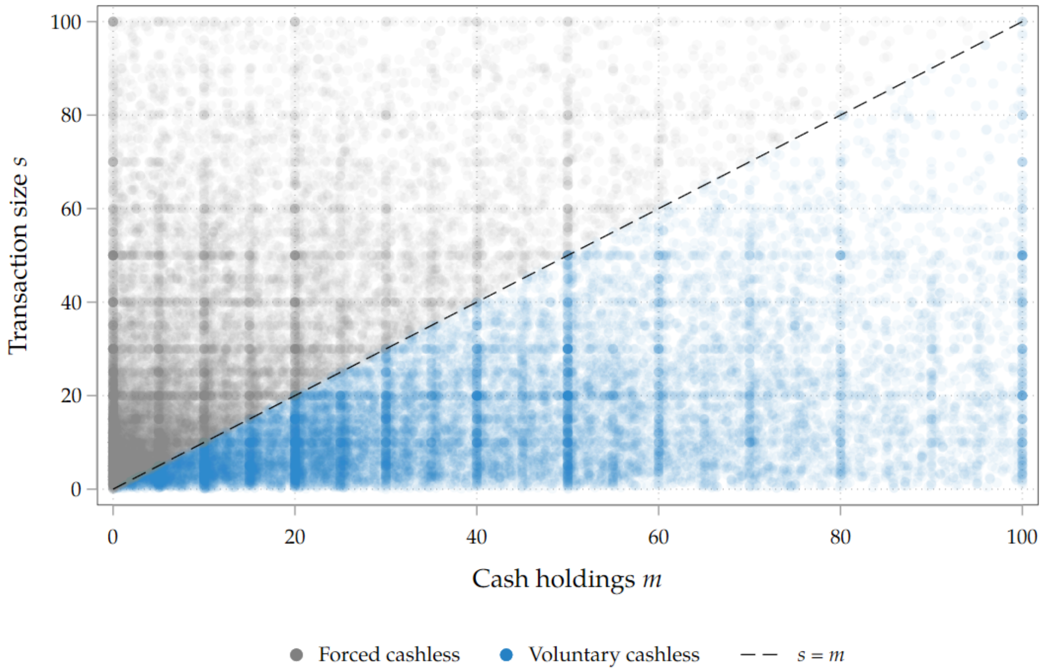
Note: Each dot is a transaction. Obs. flagged in orange are not coherent with TS policies, i.e., either i) the agent voluntarily used cash to settle a transaction bigger than her largest voluntary cashless payment, or ii) the agent voluntarily used a cashless payment method to settle a transaction smaller than her smallest voluntary cash payment. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

A.2 Existing theoretical models and transaction-level data

It is possible test the predictions of Whitesell (1989) and Alvarez and Lippi (2017) using SUCH and SPACE data, as transaction sizes, cash holdings and payment methods chosen are simultaneously observed for each purchase.

In particular, since I observe more than one payment (sometimes as much as eight) for a large share of people, it is possible to test the transaction size threshold policies by Whitesell (1989) even allowing the threshold $\bar{s}$ to be heterogeneous. If thresholds are individual-specific and given by $\bar{s}_i$, according to the model one should never observe an individual performing a voluntary cash payment which is larger than her biggest voluntary cashless payment. Figure 13 shows that a large share of people explicitly violate transaction size threshold policies. Given that payment diaries in the data are only one day long, one can expect to see much more agents violating such rules as the observation time horizon is extended. Of course, this does not mean that the theory is invalid: as explained in the text, Whitesell (1989) manages to explain the observed negative correlation between transaction sizes and the likelihood of cash payments. The purpose of comparing it the predictions of the model with individual level data is just to argue that transaction sizes are only a part of the story.

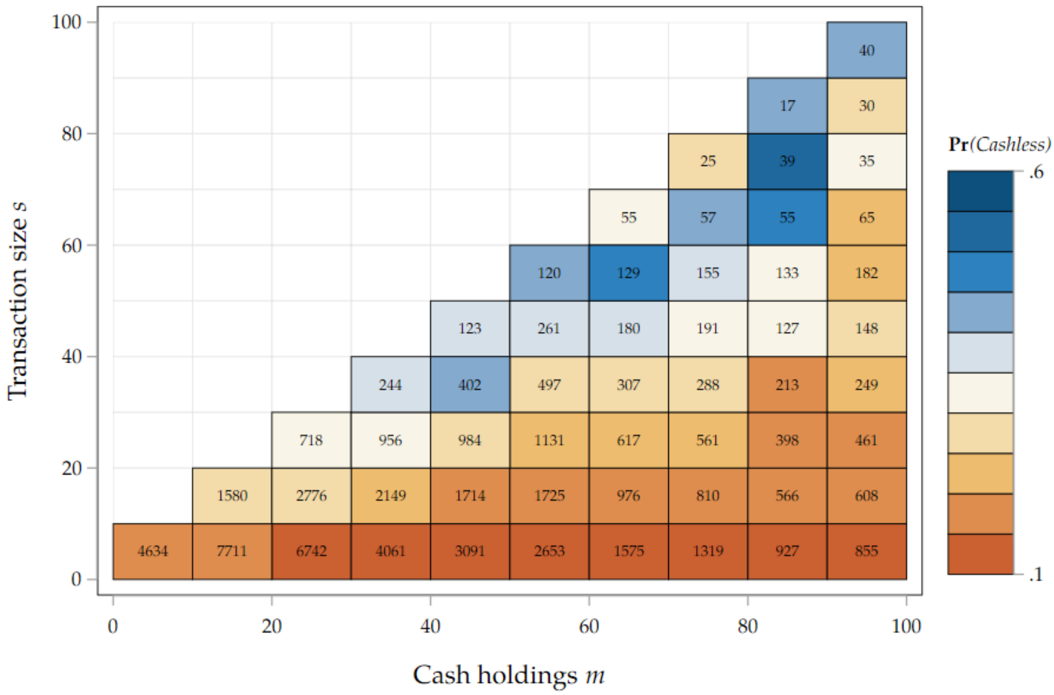
FIGURE 14: Payment method choices, individual transactions.



Note: Each dot is a transaction reported in payment diaries. Above the 45 degree line, all payments must be settled using cards (m < s). The blue dots below the 45 degree line represent voluntary cashless payments, i.e., transactions where cashless payments were employed even if the agent had sufficient cash to pay. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

I now analyze the cash burns policies obtained by Alvarez and Lippi (2017). Despite being quite accurate for very small payments, Figure 14 shows that *cash burns* policies cannot rationalize a sizeable share transactions which are bigger in size, for which agents often employ cashless methods even if they have enough cash on hand. Observe that this is not a violation of results from Alvarez and Lippi (2017), as the optimal policies derived in the paper are only applicable for very small transaction amounts, as the authors point out directly, since the expenditure stream in their model is infinitesimal. Therefore, it should not be surprising that cash burn policies do not match the data when $s \gg 0$: the authors themselves acknowledge that their explanation is "complementary to that based on transaction size" (as in Whitesell (1989)) and "only able to address the choice of means of payment for small-sized transactions". Despite this, cash burns policies have been employed even in models with heterogeneous transaction sizes, without proving their optimality in this new setting. For instance, Arango, Bouhdaoui, et al. (2014) assume that agents follow a generalized cash burn policy: they use cash whenever they have enough, but use their card when they incur in a transaction which is too big. Even in their model, agents never use cards when they have enough cash to carry out a payment, contradicting the data. In this paper, I show that generalized cash burn policies are not optimal in a model with heterogeneous transac-

FIGURE 15: Share of cash payments for different m and s for agents that reportedly prefer to use cash or are indifferent between using cash or cashless methods.

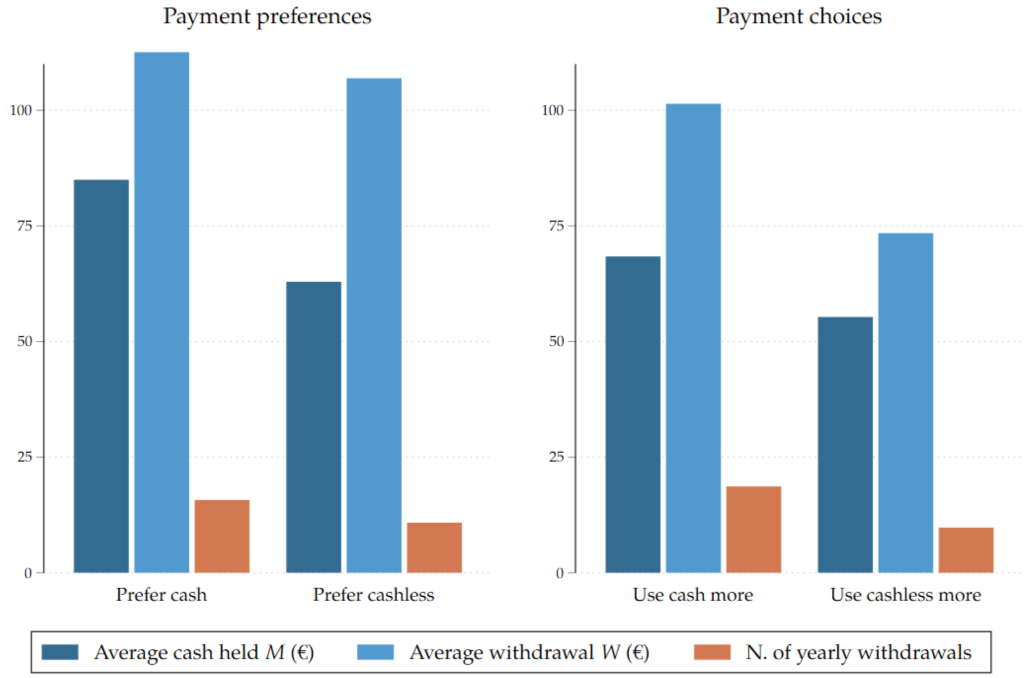


Note: Each dot is a transaction reported in payment diaries. Above the 45 degree line, all payments must be settled using cards (m < s). The blue dots below the 45 degree line represent voluntary cashless payments, i.e., transactions where cashless payments were employed even if the agent had sufficient cash to pay. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

tion sizes.

One might wonder whether cashless usage when cash on hand is abundant is driven by people that simply prefer to pay cashless, independently of the size of the transaction or on the amount of cash holdings: after all, cashless payments are easy, safe and fast. This seems unlikely to be the only explanation: if that was the case, why should the probability of cashless payments change so much across different values of m and s when cash is sufficient to carry out the transaction? However, I can provide further evidence that this type of behavior (using cashless methods when the cash in advance constraint is not binding) is not driven by preferences. Exploiting answers to the SUCH and SPACE survey questionnaires that ask people about their preferred payment methods, in Figure 15 I replicate the plot in Figure 1 but only for people that reportedly prefer to use cash or that are indifferent between using cash and cashless. We see that, clearly, still a lot of transactions are carried out using cards even when it is not necessary to do so.

Figure 16: Payment preferences, payment choices and cash management policies.



Note: This graph displays cash management policies across groups of individuals defined according to their payment preferences (on the left) and to their payment behavior in the day of the diary (on the right). *Source: ECB SUCH (2016) and SPACE (2019) Data.*

A.3 Payment behavior and cash management patterns

As the previous literature extensively discussed[23], there is a mutual relationship between payment and cash management choices: on one hand, people might manage their cash in a different way based on how much they use cashless payments; at the same time, when choosing on how to pay people might take into account the impact of their decision on future cash holdings.

Let's first look at how payment preferences and choices impact cash management strategies. Figure 16 provides further evidence on the existence of this channel. In the left panel of the Figure, I look at cash management behavior across groups defined in terms of expressed payment preferences, which agents are asked about in the survey questionnaire and which are coherent with observed choices in the diary, as will be shown later on. It is possible to see that people who reportedly prefer to pay with cash will have higher average cash holdings, withdraw more often and perform larger withdrawals than people who state they prefer to pay cashless. In the right panel, I divide people in groups based on the payment method they used more often during the day of

[23]There is a large body of papers making the claim that cash management and payment choices should be studied jointly as they mutually affect each other. Applied papers making this claim are Bagnall et al. (2016) and Wang and Wolman (2016). As said in the previous Section, theoretical payment choice models usually feature a cash management problem.

the diary and I obtain similar results. These plots suggest that people choose their cash management strategy taking into account their payment choice habits/preferences.

B Theoretical model

B.1 Proofs

Proof of Proposition 1

Proof. For agents with $\kappa > 0$, the ex-ante optimal amount of money at $t = 2$ is given by

$$m^* = \arg\min_{m_2} V_2(m_2) = \arg\min_{m_2} Rm_2 + (1 - F(m_2)) (\phi\kappa + (1-\phi)u) .$$

Taking the first order conditions we obtain

$$R - f(m) (\phi\kappa + (1-\phi)u) = 0, \quad \Longrightarrow \; f(m) = \frac{R}{\phi\kappa + (1-\phi)u}.$$

Notice that F strictly concave implies that $f(m)$ is strictly decreasing. This implies that the equation has either zero solutions (if $f(0) < R/ (\phi\kappa + (1-\phi)u)$) or one solution (if $f(0) \geq R/ (\phi\kappa + (1-\phi)u)$). If $f(0) \geq R/ (\phi\kappa + (1-\phi)u)$ a solution must exist, otherwise $\int f(s)ds > 1$ and $f(s)$ would not be a pdf. The solution is going to be a local minimum if and only if

$$-(\phi\kappa + (1-\phi)u) f'(m) > 0, \quad \Longrightarrow \; f'(m) < 0.$$

Since $f(m)$ is a strictly decreasing function of m, $f'(m) < 0$ for all m and therefore the objective function is strictly convex, which guarantees that the local minimum is also the unique global minimum, which is going to be given by

$$m^* = f^{-1}\left(\frac{R}{\phi\kappa + (1-\phi)u}\right).$$

When the first order conditions have no solutions, the objective function is monotonically increasing for all $m \geq 0$. Therefore, for this region of parameters optimal cash holdings will be given by $m^* = 0$. ■

Proof of Proposition 2

Proof. Define the function

$$G : [0, m^*] \to \mathbb{R}, \quad m \mapsto G(m) := Rm - (\phi\kappa + (1-\phi)u) F(m).$$

The problem can then be rewritten as

$$V(m) = \min\{G(m), b + G(m^*)\}.$$

Notice that

1. G is twice continuously differentiable;
2. $G(0) = 0$;
3. $G'(m) < 0$ for all $m \in [0, m^*]$. Indeed, note that $G'(m) = R - f(m)(\phi\kappa + (1-\phi)u)$. Therefore

$$\begin{aligned} G'(m) < 0 &\implies R - f(m)(\phi\kappa + (1-\phi)u) < 0 \implies f(m) > \tfrac{R}{(\phi\kappa + (1-\phi)u)} \implies \\ &\implies m < f^{-1}(R/(\phi\kappa + (1-\phi)u)) \implies m < m^*. \end{aligned}$$

This implies that, if there exists $\overline{m}$ such that $G(\overline{m}) = b + G(m^*)$ (so that individuals are indifferent between withdrawing or not at $m = \overline{m}$), it must be that $G(m) > b + G(m^*)$ for all $m \in [0, \overline{m}]$, i.e., that $w(m) = m^* - m$ for all $m \in [0, \overline{m}]$. Finally, one needs to show that such $\overline{m}$ exists. As $G(m)$ is decreasing and continuous, so that $\lim_{m \to m^*} G(m) = G(m^*)$, a necessary and sufficient condition for the existence of $\overline{m}$ is that $G(0) > b + G(m^*)$. As $G(0) = 0$, this boils down to

$$\begin{aligned} b + G(m^*) < 0 &\implies b < -G(m^*) \implies \\ &\implies b < F(m^*)(\phi\kappa + (1-\phi)u) - Rm^*, \end{aligned}$$

as desired. ∎

Proof of Proposition 3

1. I start from proving that $p(m_1, s_1) = 0$ for all (m_1, s_1) such that $s_1 < m_1$ whenever $\kappa > \beta b$. When $m_1 < \overline{m}$, it is obviously suboptimal to use cards as long as $\kappa > 0$. If $m_1 > \overline{m}$ and $s_1 > m_1 - \overline{m}$, it is optimal to use the card when

$$\beta V(m_1) + \kappa < \beta(V^* + b),$$

i.e., when

$$V(m_1) < V^* + b - \frac{\kappa}{\beta} < V^*.$$

As $V(m) \geq V^*$ for all m, cashless usage is never optimal in this case. If $m_1 > \overline{m}$ and $s_1 < m_1 - \overline{m}$, it is optimal to use the card when

$$\beta V(m_1) + \kappa < \beta V(m - s),$$

i.e., when

$$V(m_1) < V(m-s) - \frac{\kappa}{\beta} < V^* + b - \frac{\kappa}{\beta} < V^*,$$

so that cashless usage is never optimal in this case either, as desired.

2. First, let's prove that $\exists \widetilde{m}$ that satisfies (10). By the intermediate value theorem, given that V is continuous, that $V(\overline{m}) = V^* + b$ and that $V(m^*) = V^*$, $V(m)$ will take all the values in $(V^* + b, V^*)$. If $0 < \kappa < \beta\eta$, then $V^* + b - \frac{\kappa}{\beta} \in (V^* + b, V^*)$.

   I now prove subpoints (a) and (b).

   (a) By contradiction. Suppose that for some $m_1 \in [0, \widetilde{m_1}]$, there exists some s_1 such that $p_1(m_1, s) = 1$. This would mean that

   $$\beta V(m_1) + \kappa < \beta V(m_1 - s_1),$$

   which in turn implies

   $$V(m_1) < V(m_1 - s_1) - \frac{\kappa}{\beta} \leq V^* + b - \frac{\kappa}{\beta} = V(\widetilde{m}_1),$$

   a contradiction by the fact that V is decreasing. Notice that this covers both the case $s_1 < m_1 - \overline{m}$ and the complementary one.

   (b) Let $m_1 > \widetilde{m}_1$. First, I show that for all such m the set $S(m)$ is nonempty, i.e., that there exist at least one payment size for each $m_1 > \widetilde{m}_1$ such that it is optimal to pay cashless. Simply pick $m_1 = \widetilde{m}_1 + \varepsilon$, for some $\varepsilon > 0$. I proceed by contradiction. Assume that $\forall s_1$ it is optimal to pay using cash, i.e., that

   $$\beta V\left(\widetilde{m}_1 + \varepsilon\right) + \kappa > \beta V\left(\widetilde{m}_1 + \varepsilon - s_1\right).$$

   Pick $s_1 = \widetilde{m}_1 + \varepsilon - \overline{m}$. Then, I get

   $$\beta V\left(\widetilde{m}_1 + \varepsilon\right) + \kappa > \beta V\left(\overline{m}\right) = \beta\left(V^* + b\right).$$

   Rearranging,

   $$\beta V(\widetilde{m}_1 + \varepsilon) > \beta\left(V^* + b\right) + \kappa,$$

   that can be rewritten as

   $$\beta V(\widetilde{m}_1 + \varepsilon) < \beta V(\widetilde{m}_1),$$

   which again contradicts the fact that V is decreasing in $[0, m^*]$. Call $\bar{s}(m_1) = m_1 - \overline{m}$, the transaction size that decreases current money holdings to the trigger value $\overline{m}$. I just showed that $\bar{s}(m_1) \in S(m_1)$ for all $m_1 > \widetilde{m}_1$.

   I now want to show that for any $m_1 > \widetilde{m}_1$, there exists a transaction value $\underline{s}(m_1)$ such that $p(m_1, s_1) = 1$ for all $\underline{s}(m_1) < s_1 \leq m_1$. Suppose that for

$m_1 = \widetilde{m}_1 + \varepsilon$ and every $\varepsilon > 0$, $\underline{s}(m_1)$ is given by

$$\beta V\left(\widetilde{m}_1 + \varepsilon\right) + \kappa = \beta V\left(\widetilde{m}_1 + \varepsilon - \underline{s}(\widetilde{m}_1 + \varepsilon)\right).$$

Rearranging, I obtain

$$V\left(\widetilde{m}_1 + \varepsilon - \underline{s}(\widetilde{m}_1 + \varepsilon)\right) = V\left(\widetilde{m}_1 + \varepsilon\right) + \frac{\kappa}{\beta}.$$

Notice that $V(\widetilde{m}_1 + \varepsilon) + \frac{\kappa}{\beta} < V(\widetilde{m}_1) + \frac{\kappa}{\beta} = V^* + b$. Again by the Intermediate Value Theorem, it certainly exists $\underline{s}(\widetilde{m} + \varepsilon)$ that satisfies this Equation. It is clearly the case that for any $s_1 > \underline{s}(\widetilde{m}_1 + \varepsilon)$,

$$V\left(\widetilde{m}_1 + \varepsilon - s_1\right) > V\left(\widetilde{m}_1 + \varepsilon\right) - \frac{\kappa}{\beta},$$

so that it is optimal to use cashless methods for all $s_1 \in S(m_1) = (\underline{s}(m_1), m_1)$.

Finally, I would like to show that the region of parameters characterized we are focusing on to obtain these results is non-empty. The interesting region is characterized by $\phi\kappa + (1-\phi)u \geq R/f(0)$ (to make sure that agents want to hold positive cash in period 2), by $b < \underline{b} = F(m^*)\left(\phi\kappa + (1-\phi)u\right) - Rm^*$ (to make sure that agents withdraw for low levels of cash holdings at the start of period 2) and by $\kappa < \beta b$ (to generate voluntary cashless usage). First, notice that the second condition can be rewritten as a function of κ as

$$\kappa > \frac{b + Rm^* - F(m^*)(1-\phi)u}{\phi F(m^*)}.$$

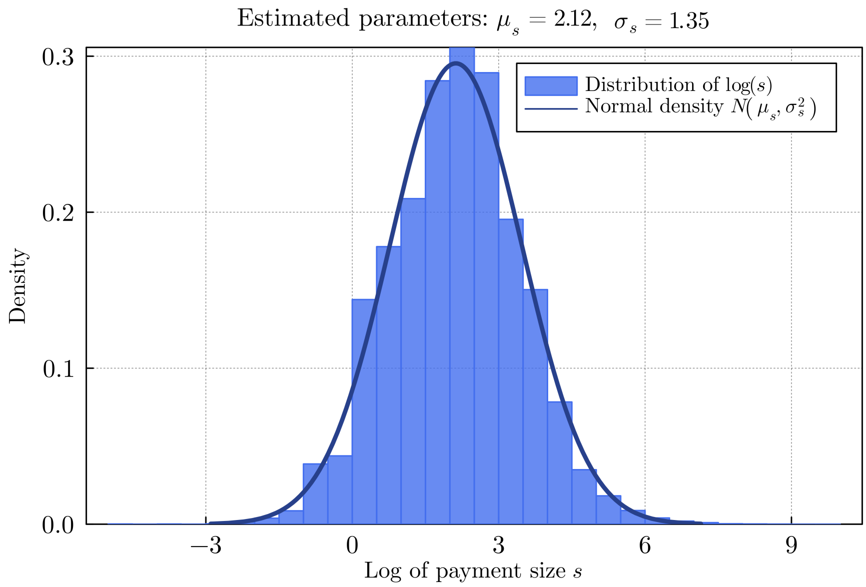
Fix κ at a certain level and pick b such that $\kappa < \beta b$. It's easy to make the above equation, as well as the first constraint hold by increasing u. For any $(R, \kappa, \beta, \phi, F(\cdot))$ and for any b such that $\kappa < \beta b$, it always exists u large enough that all constraints are satisfied.

C Quantitative model

C.1 The distribution of transaction sizes s

The transaction size distribution is a key object in the model, as it influences choices of agents via expected outflows of cash in the future. In principle, one could specify the distribution nonparametrically, matching the relative frequency of each transaction size observed in the data. I take a different route, exploiting the observation from Boeschoten (1992) that the distribution of transaction sizes is approximately lognormal. I investigate whether this is an appropriate assumption using all transactions in SUCH and SPACE data (more than 175,000 payments). As Figure 17 shows, it turns out the $\log(s) \sim N(\mu_s, \sigma_s^2)$, therefore $s \sim LN(\mu_s, \sigma_s^2)$ appears to be an appropriate assumption. To estimate the distribution of transactions in the whole SUCH and SPACE

Figure 17: Distribution of transaction sizes and normal density.



Note: This graph is based all transactions in the data (176,339 payments). It displays the histogram of log payment sizes with an overlaid normal fit; estimated parameters of the normal distribution are also displayed. *Source: ECB SUCH (2016) and SPACE (2019) Data.*

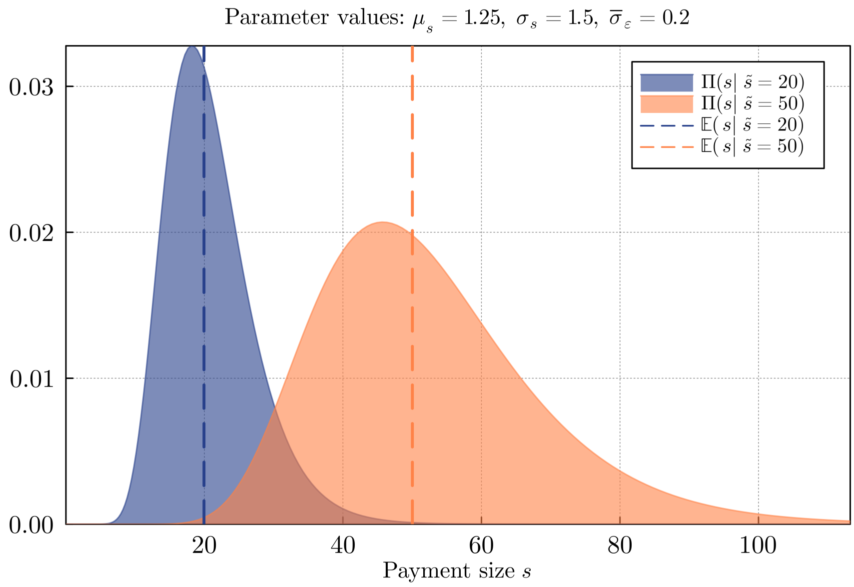
set of countries, one can simply pick μ_s and σ_s^2 to match the mean and variance of log payments. Estimated parameters for this *aggregate* transaction size distribution are displayed in Figure 17. When estimating the model for single countries, I will calibrate μ_{si} and σ_{si} for every country i, in order to account for differences in prices and expenditure habits that people from different European countries might have. I plot all the estimated distributions of transaction sizes in Figure 24.

C.2 The distribution of transaction signals $\tilde{s}$

From transaction signals to actual transactions. As explained in Appendix C.1, it is reasonable to assume that transaction sizes are lognormally distributed, i.e., that $s \sim LN\left(\mu_s, \sigma_s^2\right)$. In the quantitative model, agents receive signals $\tilde{s}$ that are potentially informative about the size of the next purchase. It makes sense to assume that transaction signals are also lognormally distributed[24], i.e., that $\tilde{s} \sim LN\left(\mu_{\tilde{s}}, \sigma_{\tilde{s}}^2\right)$. For each transaction t, I hypothesize that the actual transaction size s_t is given by the signal $\tilde{s}_t$

[24]This is consistent with my interpretation of signals: when agents receive a transaction signal, they realize they need to buy something. Usually, people knows the kind of good or service they need to buy, and they have an expectation on the price they will pay for it. If actual payments are lognormally distributed, it makes sense that agents signals on the size of their next payments are lognormally distributed as well.

FIGURE 18: Conditional distribution $\Pi(s|\tilde{s})$ for different signals.



multiplied by a *transaction size surprise* ε_t with mean one, in the following way

$$\begin{aligned} & s_t = \tilde{s}_t \cdot \varepsilon_t, \\ & \varepsilon \sim LN\left(\mu_\varepsilon, \sigma_\varepsilon^2\right), \\ & \mathbb{E}(\varepsilon) = \exp\left(\mu_\varepsilon + \frac{\sigma_\varepsilon^2}{2}\right) = 1 \implies \mu_\varepsilon = -\frac{\sigma_\varepsilon^2}{2}. \end{aligned} \tag{17}$$

Notice that I impose that signals are on average right, i.e., that $\mathbb{E}(\varepsilon) = 1$. It would make no sense to allow agents to consistently underestimate or overestimate the size of their next purchase, as there would be no way to identify such expectational error with the available data.

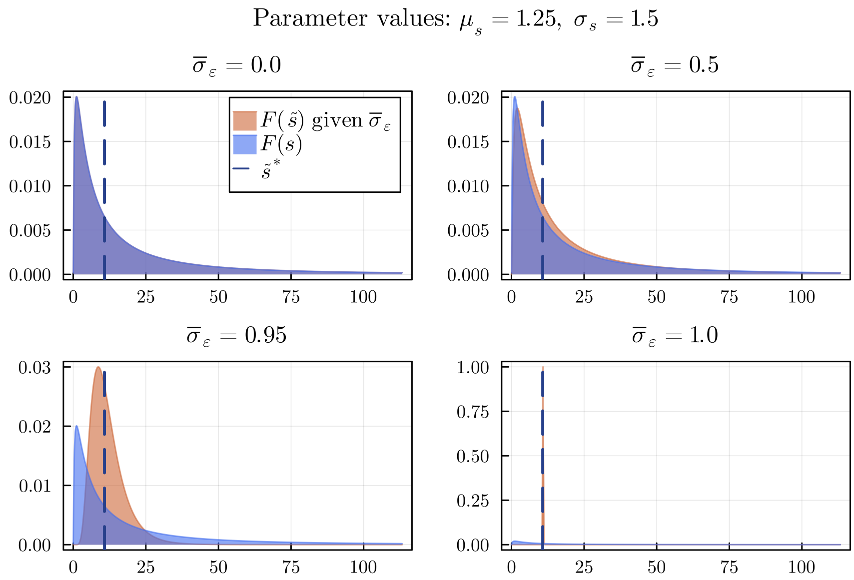
Signal precision and the distribution of signals. For computational convenience, I also impose that ε is independent of $\tilde{s}$. Notice from Figure 18 that this does not mean that all signals are equally precise: as the shock ε is multiplicative, the forecast error will be smaller for smaller payments[25]. As the product of independent lognormal distributions is also lognormal, we have that $s \sim LN\left(\mu_s, \sigma_s^2\right) = LN\left(\mu_{\tilde{s}} + \mu_\varepsilon, \sigma_{\tilde{s}}^2 + \sigma_\varepsilon^2\right)$. Notice that μ_s and σ_s can be calibrated directly from data on transactions, as they have to match mean and variance of the distribution of log payment sizes[26]. Therefore, because of the restriction imposed on μ_ε in (17), we end up with the following two equations

$$\mu_{\tilde{s}} = \mu_s + \frac{\sigma_\varepsilon^2}{2}, \tag{18a}$$

[25]The reason for this modeling choice is also intuitive. Suppose that agent i receives the signal that she needs to buy a coffee very soon, while agent j receives the signal that he will go shopping for a new fridge. Clearly, the absolute uncertainty on the final amount of money needed to settle the transaction is much higher in case one needs to buy a fridge, as the dispersion of prices across shops for the same good is bigger when the average expenditure for that good is higher.

[26]If $s \sim LN\left(\mu_s, \sigma_s^2\right)$, then $\log s \sim N\left(\mu_s \sigma_s^2\right)$. Therefore, $\mathbb{E}(\log s) = \mu_s$ and $\mathrm{Var}(\log s) = \sigma_s^2$.

FIGURE 19: Distribution of signals $F(\tilde{s})$ for different levels of relative noise $\overline{\sigma}_{\varepsilon}$.



$$\sigma^2_{\tilde{s}} = \sigma^2_s - \sigma^2_{\varepsilon}, \tag{18b}$$

that illustrate that for a given choice of signal noise σ^2_{ε} the parameters of the transaction signals distribution $\tilde{s} \sim LN(\mu_{\tilde{s}}, \sigma^2_{\tilde{s}})$ are uniquely pinned down.

Relative noise. Notice that by construction $\sigma_{\varepsilon} \leq \sigma_s$, as $\sigma_{\tilde{s}}$ needs to be nonnegative. Define *relative noise* as

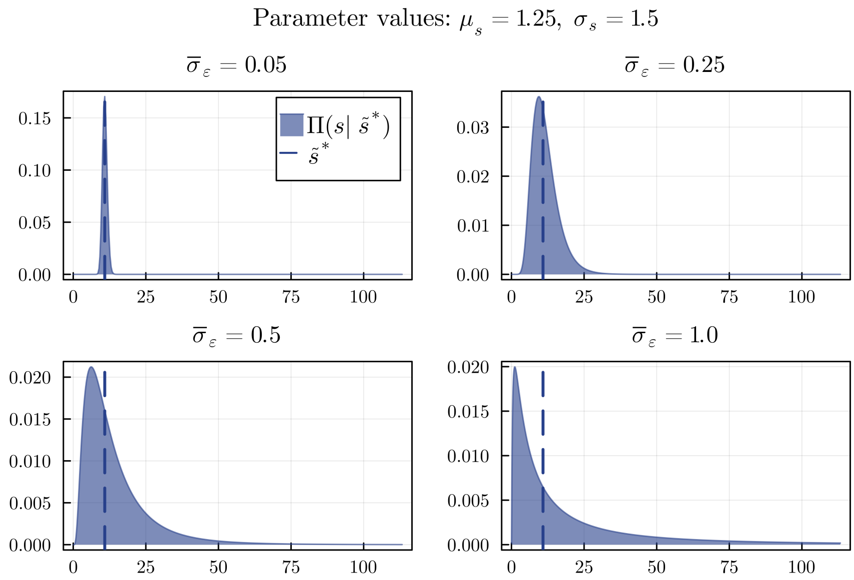
$$\overline{\sigma_{\varepsilon}} = \frac{\sigma_{\varepsilon}}{\sigma_s},$$

i.e., the ratio between noise and its highest possible value: this clearly implies that $\overline{\sigma_{\varepsilon}} \in [0, 1]$. This relative measure of signal precision is more easily interpretable than the absolute one, which also depends on the variance of the payment size distribution, and it allows comparisons between signal noise levels of agents exposed to different distributions of transaction sizes.

Perfect and non-informative signals. The extreme cases of $\overline{\sigma}_{\varepsilon} = 0$ and $\overline{\sigma}_{\varepsilon} = 1$ are helpful in understanding how the signal structure of the model works. When $\overline{\sigma}_{\varepsilon} = 0$ ($\sigma_{\varepsilon} = 0$, *perfect signals*), also $\sigma_{\varepsilon} = 0$ and from (18) we have that $\mu_{\tilde{s}} = \mu_s$ and $\sigma^2_{\tilde{s}} = \sigma^2_s$. As shown in the top left panel of Figure 19, in this case the distribution of signals and that of transactions are exactly identical. and signals are perfectly informative. This is equivalent to a model in which agents know the transactions sizes before withdrawing, as in Briglevics and Schuh (2021). The top left panel of Figure 20 shows that for very low $\overline{\sigma}_{\varepsilon}$, the conditional distribution $\Pi(s|\tilde{s})$ becomes extremely concentrated around $\tilde{s}$. For the extreme case $\overline{\sigma}_{\varepsilon} = 0$, we have that $\Pi(s|\tilde{s}) = \mathbb{1}_{s=\tilde{s}}$.

When instead $\overline{\sigma}_{\varepsilon} = 1$ ($\sigma_{\varepsilon} = \sigma_s$, *non-informative signals*), we have that $\sigma^2_{\tilde{s}} = 0$ and that $\mu_{\tilde{s}} = \mu_s + \sigma^2_s/2$. This means that the transaction size distribution becomes degenerate, i.e., there is only one possible signal given by $\tilde{s}^* = \mathbb{E}(\tilde{s}) = \exp\left(\mu_s + \sigma^2_s/2\right)$. Since $s \sim$

FIGURE 20: Conditional distribution $\Pi(s|\tilde{s}^*)$ for different levels of relative noise $\overline{\sigma}_\varepsilon$.



$LN\left(\mu_s, \sigma_s^2/2\right)$, we know that $\mathbb{E}(s) = \exp\left(\mu_s + \sigma_s^2/2\right)$. Therefore, the unique possible signal when $\overline{\sigma}_\varepsilon = 1$ corresponds to the expected transaction size, i.e, $\tilde{s}^* = \mathbb{E}(s)$. Of course, in this case receiving the signal yields no additional information about the next payment, as everyone receives it: this situation is equivalent to a world in which there are *no signals*, and everybody has the same information about future payments when withdrawing, i.e., they just now the unconditional distribution $F(s)$.

C.3 Multinomial logit for acceptance rates

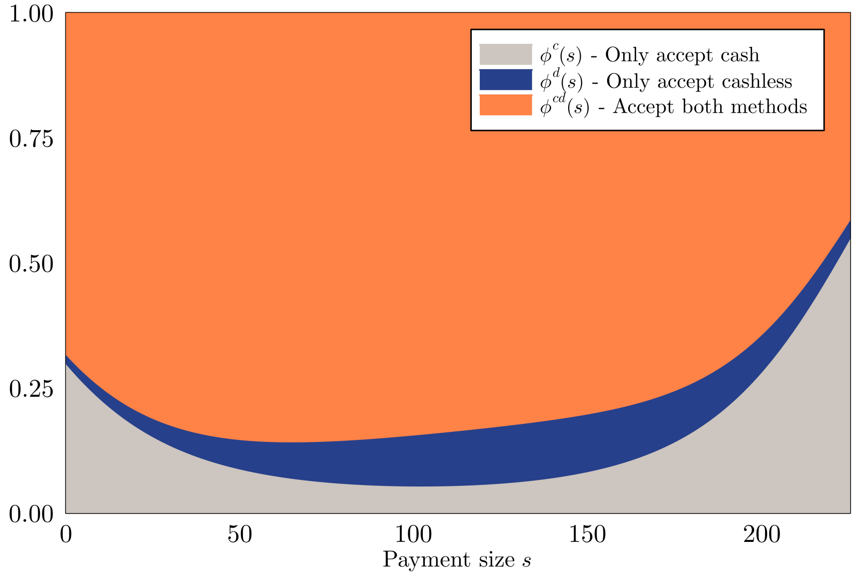
Let $\mathbf{\Phi}_t$ represent the payment method acceptance choice of the merchant for transaction t in the data. There are three possibilities: it could be that the shop only accepts cash (c), that it accepts only cashless methods (d) or that it accepts both payment methods (cd). In short, $\mathbf{\Phi} \in \{c, d, cd\}$. In the model, I assume that the acceptance decision of merchants is merely a function of the size of the transaction s. In particular, I denote the probability that a merchant will adopt acceptance regime $\mathbf{\Phi} = j$ for a given transaction size s as

$$P\left(\Phi = j|s\right) = \phi^j(s).$$

For instance, $\phi^c(s)$ represents the probability to meet a merchant that accepts only cash for a transaction of size s. In practice, I estimate $\phi^j(s)$ for all j using a multinomial logit model of the type

$$\phi_t^j = P\left(\mathbf{\Phi}_t = j|s_t\right) = \frac{e^{\beta_0^j + \beta_1^j s_t + \beta_2^j s_t^2}}{\sum_{l\in\{c,d,cd\}} e^{\beta_0^l + \beta_1^l s_t + \beta_2^l s_t^2}}, \tag{19}$$

FIGURE 21: Multinomial logit for payment method acceptance choices: predicted probabilities of each *acceptance regime* as a function of transaction sizes s.



Note: In this Figure, I use the entire SPACE sample (50594 transactions). Each data point is a transaction, for which I observe: the size of the transaction s, the payment method employed to carry it out and whether the alternative payment arrangement was accepted as well. The latter two pieces of information enable me to back up the *payment acceptance set* of merchants involved in each reported transaction.

with the usual normalization $\boldsymbol{\beta}^{cd} = \mathbf{0}$. After estimating $(\beta_0^c, \beta_1^c, \beta_2^c, \beta_0^d, \beta_1^d, \beta_2^d)$ using maximum likelihood, I get the estimated probabilities

$$\phi^c(s) = \frac{e^{\beta_0^c+\beta_1^c s+\beta_2^c s^2}}{1+\sum_{l\in\{c,d\}} e^{\beta_0^l+\beta_1^l s+\beta_2^l s^2}}, \tag{20}$$

$$\phi^d(s) = \frac{e^{\beta_0^d+\beta_1^d s+\beta_2^d s^2}}{1+\sum_{l\in\{c,d\}} e^{\beta_0^l+\beta_1^l s+\beta_2^l s^2}}, \tag{21}$$

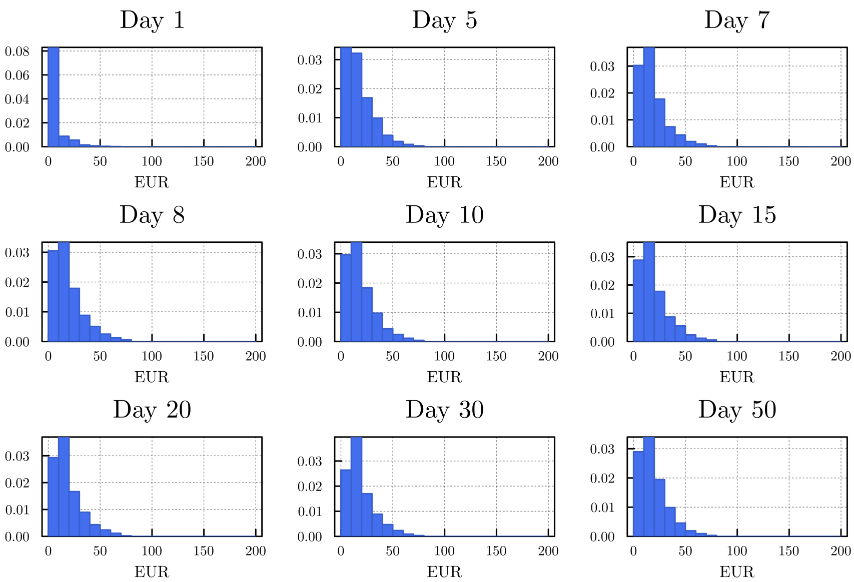
$$\phi^{cd}(s) = \frac{1}{1+\sum_{l\in\{c,d\}} e^{\beta_0^l+\beta_1^l s+\beta_2^l s^2}}, \tag{22}$$

where by design $\phi^c(s)+\phi^d(s)+\phi^{cd}(s) = 1$, for all transaction sizes s. When aggregating all transactions in SPACE data (for year 2019) I get estimates that deliver the predicted probabilities displayed in Figure 21. In the estimation procedure, I do this separately for each country, in order to get country-specific payment method acceptance profiles as a function of transaction sizes.

C.4 Length of the burn-in period

As I discussed in Subsection 4.4, at the start of the simulation I need to initialize the level of cash holdings m_{it} for each agent. An elegant solution would be to solve the discrete-time analog of Kolmogorov forward equations and analytically obtain the sta-

FIGURE 22: Distributions of cash holdings $G_d(m)$ at the end of day d.

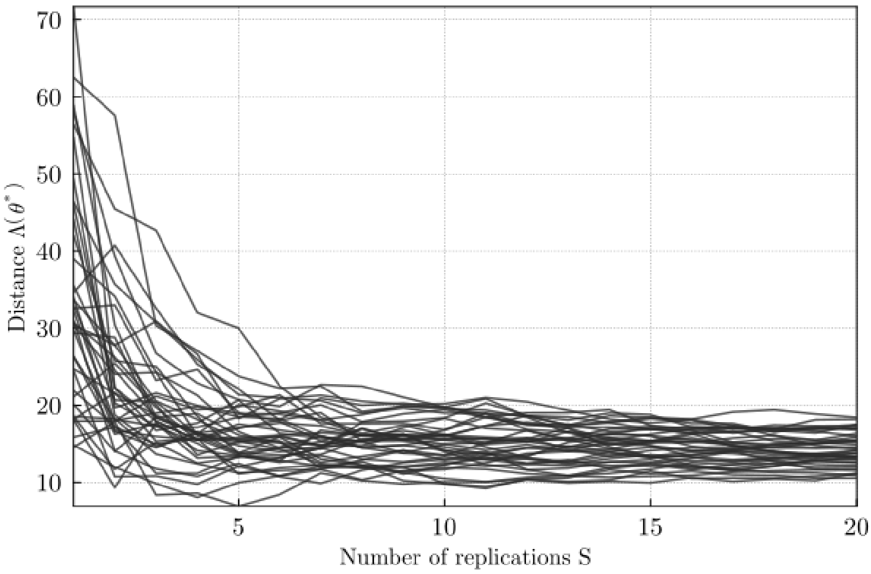


tionary distribution of cash holdings $G(m)$, but this is unfeasible given that I am dealing with a quite complicated quantitative model. An alternative solution would be to compute the stationary distribution via recursive iterations until convergence, after setting up a discretized version of the Kolmogorov forward equations. This is feasible, but extremely hard due to the existence of multiple transaction sizes. Finally, a less elegant but effective workaround is to initialize the level of cash holdings m_{it} randomly, to simulate agents choices and compute the distribution of cash holdings $G_d(m)$ at the end of each day d. If a stationary distribution $G(m)$ exists, $G_d(m)$ will converge to it for d high enough. As I am interested in choosing the day of the diary D such that the effect of random initial conditions has vanished, I need to find the minimum D such that $G_D(m)$ and $G_{D-1}(m)$ are "close enough": in other words, I am interested in the optimal length $D-1$ of the burn-in period. I do not adopt a formal concept of distributional convergence, but I rely on a heuristic approach plotting the distribution of cash holdings at the end of each day d and I inspect the plot to see after how many periods the distribution is approximately time-invariant. From Figure 22, it looks like $D = 7$ is an appropriate choice as the histogram looks stable afterwards.

C.5 Optimal number of replications

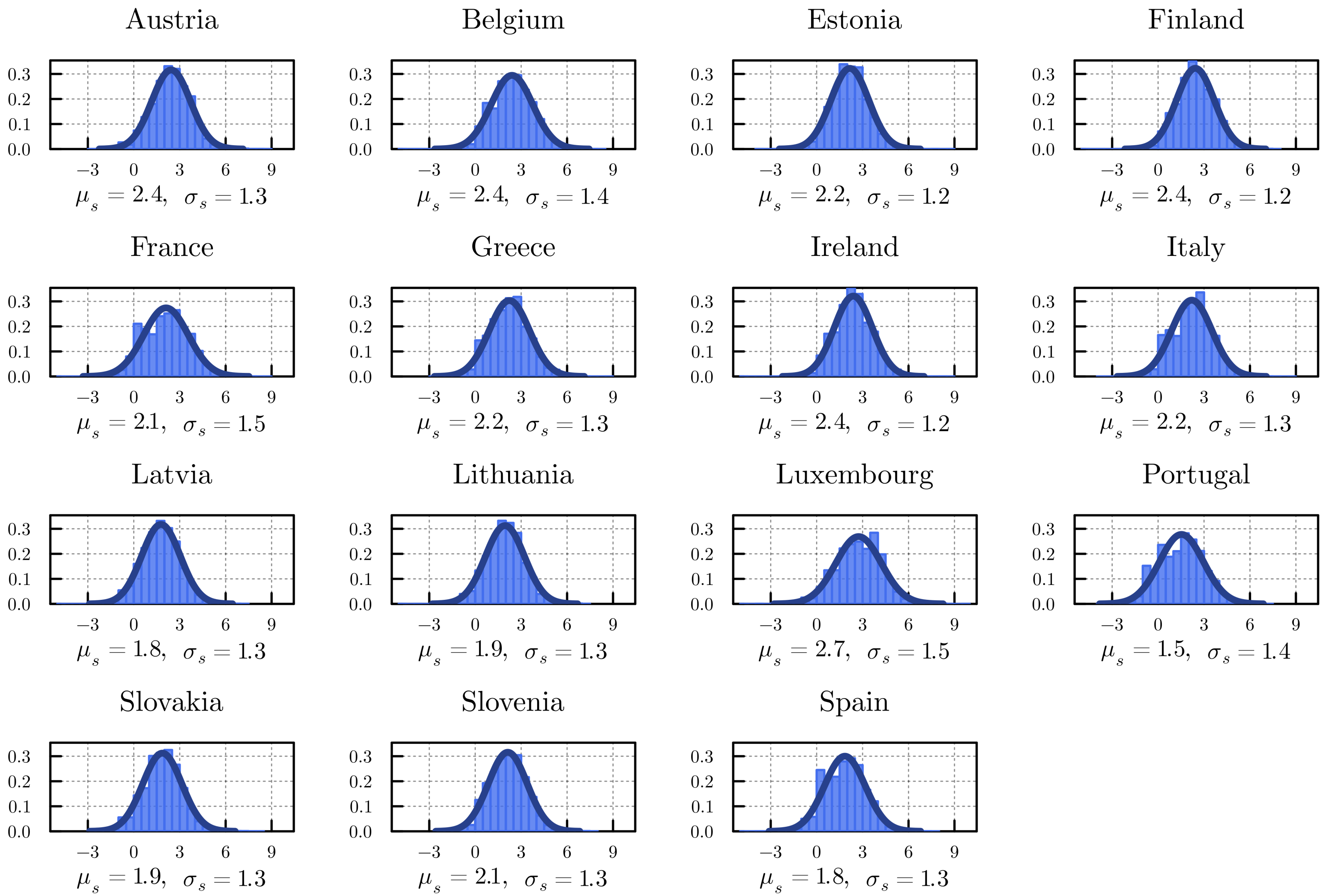
As I explain in Subsection 4.4, exploiting simulated moments that are averaged across a set of S replications improve the estimation as each function evaluation is more precise (despite being slower), since the effects of random noise that influences agents choices is averaged out by drawing the shocks multiple times. As explained in Eisenhauer, Heckman, and Mosso (2015), one should pick the number S as the smallest number of replications after which the distance function computed at the true optimum stops

FIGURE 23: The optimal number of replications S. Each line represent the evolution of the distance funtion for a given shock sequence as the number of replications increase.



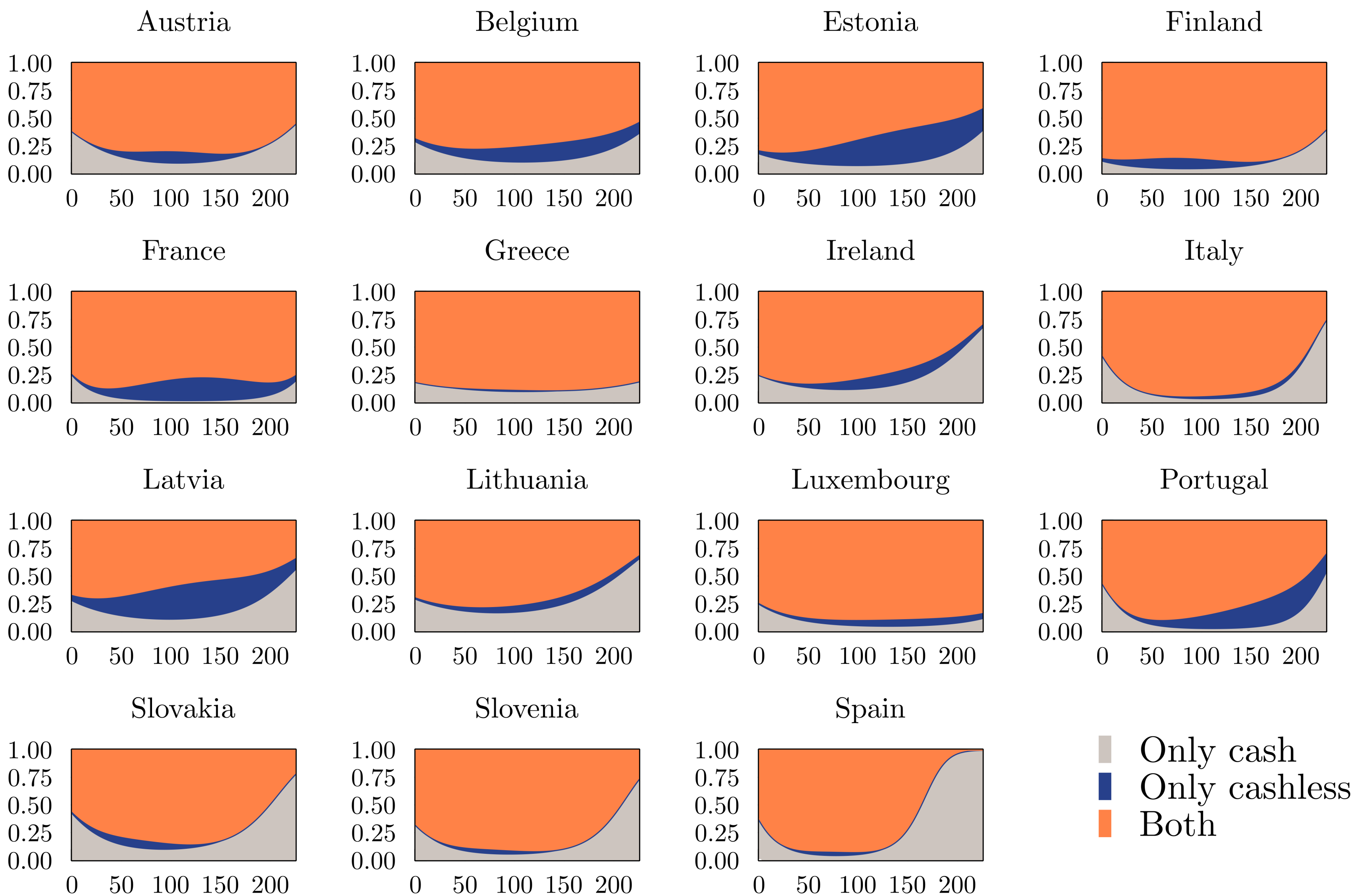
decreasing. Clearly, in order to do that one needs to pretend to know the true value of θ^* and to simulate *real* data generated by θ^*. After that, one evaluates the criterion function at the optimum, i.e., computes $\Lambda(\theta^*)$: due to noise, the value will never be exactly zero. By computing $\Lambda(\theta^*)$ for different values of S, it is possible to see how many replications are sufficient to "clean up" all the noise that can't be eliminated by replicating the simulation. Figure 23, where I repeat the above procedure several times for different shock sequences, shows that 8 to 10 simulations are enough to reach the lowest possible value of the distance function.

FIGURE 24: Distribution of transaction sizes and normal density for different countries.



Data: ECB SUCH and SPACE surveys, all transactions. Below each plot, I display the estimated parameters for each national transaction size distribution.

Figure 25: Multinomial logit for payment method acceptance choices, run by country. Predicted probabilities of each *acceptance regime* as a function of transaction sizes s.



Data: ECB SPACE Survey (2019).