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Tax evasion policies and the demand for cash

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This paper analyzes the relationship between tax evasion and the demand for cash by studying the effects of two measures to fight evasion: accessing taxpayers' bank data and imposing thresholds for cash payments. We study the effects of these policies in Italy, where visibility of bank data and cash thresholds were recently increased. We show that both significantly affected cash holdings, which grew by about 1.5 percent of the GDP. Using unique high frequency data on cash operations and exploiting regional heterogeneity in tax evasion propensity, we find that accessing bank data pushes regions with higher propensity to evade taxes to convert more deposits into cash. On the contrary, higher cash thresholds do not increase cash holdings more in these regions. We rationalize the findings with a simple model of tax evasion and payment choices, where cash and deposits have different degrees of privacy.

1. Introduction

Despite the increasing use of electronic means of payment, cash is still widely used.[1] If compared to other payment instruments, a

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[1] See Jobst and Stix (2017) and Goodhart and Ashworth (2020) for studies on the recent trends of cash demand across advanced economies. Most notably Goodhart and Ashworth (2020) identify tax evasion as one of the most important drivers for the surprising recovery of cash. See Bech et al. (2018) for a cross-country comparison of the demand for cash and cashless payments. Remarkable exceptions are Sweden and Norway, where cash in circulation is still declining.

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unique feature of cash is its complete untraceability, which is highly valuable for hiding taxable transactions and wealth.[2] While the role of tax evasion in the demand for cash has been widely explored, studies on the effects of measures to fight tax evasion on cash demand are scant.[3]

Anonymity in payments is a feature inherent to the use of cash: it provides a greater degree of privacy than other means of payment. On the contrary, the ability of different types of money to protect privacy varies, given that any payment system can shield the payee's entire information set or a subset of that information. In fact, in account-based networks, the payer's identity must be identified (Brunnermeier et al., 2021). If individuals are sensible to the number of observers, a demand for payment privacy and anonymity emerges (Borgonovo et al., 2021). In this context, the demand for privacy has two main sources: (i) a demand by individuals involved in illegal transactions, who try to reduce the probability of being incriminated (Masciandaro, 1999, Ardizzi et al., 2014b), and (ii) a demand by agents simply in search for protection from external scrutiny, not necessarily avoiding legal sanctions (Kahn, 2018). Indeed, it partially explains the emergence of new payment architectures and cryptographic procedures used to protect privacy, and the fact that they are viewed as close substitutes of cash for illegal transactions (Hendrickson and Luther, 2022). The literature on money and privacy has mainly focused on these aspects, that is, on improvement in privacy protection that leads to efficiency gains in the demand for money (Kahn et al., 2005), and recently on the introduction of central bank digital currency (Garratt and van Oordt, 2021), which can manage different degrees of financial privacy or different degrees of anonymity (Keister and Sanches, 2021). In this paper, we study tax evasion policies that interact with and alter the relative level of privacy between cash and deposits.

Reducing tax evasion is a priority for many governments,[4] especially after the surge of public debts following the recent financial and pandemic crises. The government can fight tax evasion in several ways. The literature has identified two macro-categories. The first is based on *services and values development* and sees the government as a provider of moral and monetary incentives to comply with tax payments.[5] The second follows a *coerced approach*, by which the government implements restrictions, sanctions, and strict monitoring to increase tax revenues. Regarding the latter category, while the literature has mainly focused on the elasticity of tax compliance to the level of income, tax rate, audit probability and penalty rate,[6] our paper instead focuses on an understudied empirical issue (Slemrod, 2019): the effect on cash and deposits demand of tax enforcement policies.

The first policy consists in accessing taxpayers' bank data. The literature has commonly assumed that in the event that an audit occurs, the true income is discovered without error (Chander and Wilde, 1998), but, actually, it is not the case. The taxable income expected by the government is an unobservable random variable and it has to be inferred somehow.[7] A growing literature argues that verifying taxpayer reports against third-party information is critical for tax collection.[8] In order to control the adequacy of tax compliance, the government can request access to taxpayers' bank data and infer their true taxable income.[9] Such policy obliges banks to report data on balances and transactions of their clients. The second policy is the direct limitation of cash usage for transactions. The government can set a threshold and forbid cash transactions above a certain value, a *cash threshold*. By limiting cash transactions, and accessing bank data, the government aims to reduce hidden taxable exchanges. Given the recent diffusion of cash thresholds in Europe and elsewhere and the growing possibilities related to effective financial monitoring offered by new information and big data analytics technologies, it seems important to understand the consequences of such policies for the demand of cash and deposits.

We study the effects of these policies in Italy, a country where tax evasion and cash usage are widespread[10] and where visibility of bank data to the tax revenue agency and cash thresholds have been recently increased. We estimate that accessing detailed bank data and increasing the cash threshold from 1,000 to 3,000 euro have implied an increase of cash holdings of about 1.5 percent of GDP. Using unique high frequency data on cash operations by banknote denomination, we can identify sharply the effects of changes in cash thresholds and in bank data visibility, as never done in other studies. Exploiting heterogeneity in tax evasion propensity across Italian regions, we find that making bank data visible has a higher impact on cash demand in regions with higher propensity to evade. On the contrary, higher cash thresholds do not increase cash holdings more in these regions. Using a simple conceptual framework of tax

[2] See Cagan (1958), Tanzi (1980), Schneider (1986), Ardizzi et al. (2014b) and Gordon and Li (2009). See Kahn et al. (2005) for a model on a trading economy with non-anonymous record-keeping device or anonymous money as transactions technologies. Camera (2001) explores the role of money as a facilitator of illicit actions.

[3] See for example Cagan (1958), Tanzi (1980), Schneider (1986), Ardizzi et al. (2014b), Seitz et al. (2018) and Immordino and Russo (2018a) for studies on the role of tax evasion and Antón et al. (2021) for tax enforcement.

[4] Tax evasion limits the development of fiscal capacity (Besley and Persson 2013), distorts the allocation of resources in the economy (Skinner and Slemrod 1985), and can result in a reliance on economically inefficient tax instruments (Gordon and Li 2009, Best et al. 2015).

[5] See Luttmer and Singhal (2014), Snavely (1990) and Immordino and Russo (2018a, 2018b) for a discussion on measures like tax morale improvement, tax rebates provision of better fiscal services and financial services.

[6] See Allingham and Sandmo (1972) and Srinivasan (1973), for a model of income tax evasion of rational agents under uncertainty. See Schneider and Enste (2000), Clotfelter (1983) and Slemrod et al. (2001) for some empirical studies and Slemrod and Yitzhaki (2002) and Slemrod, (2007) for a review. Cagan (1958), Tanzi (1980, 1983) and Rogoff (1998) are interested in capturing the effect of a higher tax burden on cash holdings.

[7] The literature has mainly focused on the expectation of the taxpayer about her liability (see Scothmer and Slemrod, 1989 and Alm et al., 1992) rather than investigating the expectation of the government on taxpayers' income and liability.

[8] Enforcement based on third-party information is often considered the primary mechanism by which modern governments can collect taxes (Long and Swingden 1990, Slemrod 2008, Kleven et al. 2011, and Gillitzer and Skov 2013)

[9] Third-party institutions can be employers, banks, investment funds and pension funds, see Kleven et al. (2016) and Carrillo et al. (2017). Banking data can be a powerful tool to predict tax evasion, see Artavanis et al. (2016). They use microdata on household credit to infer individuals' true and unreported income.

[10] See respectively Schneider et al. (2015) and Esselink and Hernandez (2017).

evasion and payment choices, we show that bank data visibility affects mostly the *illegal store-of-value demand* for cash to hide funds from the government's eye. Indeed, taxpayers can make offsetting adjustments (Kane, 1981): when monitoring is improved for non-cash types of transactions and wealth, cash is there to take their place. On the contrary, the *legal transactions demand* by agents adapting their cash inventories (Baumol, 1952; Tobin, 1956) seems to drive the reaction of cash holdings triggered by variations of thresholds. It is also shown that both policies involve the demand for large banknotes, which are at the center of an intense policy debate on potential limitations and elimination of cash (Gesell, 1916; Eisler, 1932; Buiter, 2009; Goodfriend, 2000; Rogoff, 2014, 2017; Humphrey, 2016; McAndrews, 2020; Lastrapes, 2018; Garin et al. 2021).

Our evidence contributes to four branches of the literature. First, concerning monetary economics and banking, we identify a new driver for currency in circulation and show that it is a very important predictor of currency in circulation and thus M0. We show that the supply of cash by the central bank and deposits by commercial banks or other financial institutions must take into account the actions of the government to monitor private money balances or limit public money payments. In particular, we estimate that about 2 percent of deposits are converted into cash, shrinking retail funding and potentially credit growth for commercial banks. Second, our evidence highlights the higher value attached to the anonymity provided by cash when advancements in information technology allow to manage huge big financial data, which is relevant for the economics of privacy.[11] Third, we inform about the effects of tax evasion policies and relate to the recent studies on the interaction between regulations about cash and cashless instruments and illegal activities.[12] Finally, from a methodological perspective, the paper shows that granular data on cash operations, combined with high frequency econometrics, can be used effectively to uncover new relevant determinants of cash in circulation, and better understand the behavior of taxpayers, outperforming commonly used low frequency-aggregate panel data estimates.[13]

The rest of the paper is organized as follows. Section 2 details the Italian institutional background and the measures adopted by the government. Section 3 provides a simple conceptual framework that connects tax evasion and payment choices when privacy of cash and cashless instruments differ and can be altered. Section 4 describes the empirical results on the effects of bank data visibility and cash thresholds on the demand for cash. Section 5 investigates the effects of the policies across regions with different tax evasion propensity. Section 6 concludes and discusses policy issues.

2. Institutional background

In this section, we provide a concise description of the two tax evasion policies that were implemented in Italy in 2015 and 2016. More details are provided in Section A of the online appendix.

Accessing Bank Data. In order to control the adequacy of tax compliance, the government can request access to "third-party information".[14] One way to reach this goal is getting data on deposits and monitoring bank accounts of potential evaders. In practice, this type of regulation imposes banks to report electronic transactions and balances of their clients to the tax revenue agency. The tax revenue agency can check for consistency between bank data and the income reported by the taxpayer. Should these two items be inconsistent, the authority could investigate more in detail whether taxes were evaded. At the beginning of 2015, the information available to the tax revenue agency was expanded. Financial intermediaries were obliged to transmit the average daily balances, in addition to the start of the year and the end of the year deposit balances and total amount of transactions (both debit and credit).[15] Furthermore, the tax revenue agency had the possibility of recovering single transactions during investigations.

Cash Thresholds. The cash threshold establishes the maximum amount for a taxable transaction that can be settled in cash. Above the threshold it is mandatory to use traceable cashless instruments.[16] Violators are punished with a substantial fine. The political economy of this policy is quite straightforward. It is seen as a way to fight tax evasion and money laundering (Riccardi and Levi, 2018). Russo (2022) provides useful information on the political parties that changed it, and a discussion on thresholds as a political tool. At the beginning of 2016 the threshold increased from 1,000 to 3,000 euro.

The laws introducing the two policies in 2015 and 2016 did not include other relevant policy changes that could confound the effects on cash demand. There is no official data on the effectiveness of these policies, like the number of fines or tax evaders caught. The increase of cash thresholds did not change its enforcement: if an officer detects any transaction above the threshold, she can fine the counterparties. The access to bank data instead required a new technological innovation to collect and store all the data, which was not in place when it became law. However, the practical implementation date and the specific dates when measurement takes place do not matter at all, because the law required banks to provide data retrospectively on the full year. Regarding anticipation effects, we

[11] See Acquisti et al. (2016) for a discussion.

[12] See Sands et al. (2017), Wright et al. (2017), Alvarez et al. (2022), Hess (2021), Das et al. (2022), Giammatteo et al. (2022) and Russo (2022). Another related paper is Slemrod et al. (2017). It studies the impact of information on business receipts by credit-card companies in US, which makes income tax evasion using credit cards less attractive and, like the access to bank data studied here, evasion using cash more attractive. The authors have no data on cash usage or holdings, though, so they cannot measure the extent of substitution between cash and cashless payment instruments.

[13] See Judson (2017) for an insightful discussion of different data sources available to study cash demand.

[14] See also Kleven et al. (2016) and Carrillo et al. (2017).

[15] The average daily balances made the reporting effective because they do not allow a potential tax evader to elude controls, withdrawing the excess balance before its measurement and depositing it back at a later point.

[16] Multiple payments to the same recipient in a short period of time are also forbidden if their total is above the threshold. The threshold is only for transactions between agents that exchange services or goods, it does not concern withdrawals or deposits of cash against deposits (for which there is no tax to pay).

would expect the cash thresholds to induce an immediate change in holdings from its implementation date. Agents may start adapting their payment behavior before, but there is no real incentive in doing so, as the supply of banknotes is not limited and there is no exchange rate with deposits. Given that bank data was collected retrospectively, withdrawing in advance does not change the relevant information available to the tax revenue agency. Nevertheless, uncertainty or ignorance about the details of the implementation of the policy may have pushed some agents to withdraw funds form their bank accounts in advance when newspapers started to talk about this policy few weeks before it became law. This is not a big concern for the analysis because the anticipation effects work against a significant effect of the policy. In Section 4 we use high frequency data and endogenous structural break tests to see whether the policies impacted cash holdings in a sharp or smooth way. On average, estimate break dates are close if not coincident with the implementation dates, with cash thresholds generating sharper changes in net cash withdrawals, as expected. In the next section, we introduce a simple conceptual framework for payment choices of tax evaders and compliers under different degrees of privacy for cash and cashless payments that can represent more formally how these policies affect agents' behavior and help us formulate the main predictions to test empirically in the following sections.

3. Main predictions on the effects on cash demand

3.1. Assumptions on privacy and payment choices of tax evaders and compliers

Suppose that there are two types of agents in the economy: tax evaders (E) and compliers (C). Compliers are extremely risk adverse, always declare and pay taxes on every transaction and stick to the rules, while evaders try to minimize the tax burden by hiding their transactions.[17] Any transaction can be declared or not. There are two possibilities of settling a transaction: using cash or cashless instruments that use deposits.[18] Cash and cashless instruments fundamentally differ in terms of privacy: they can be observed respectively with probability $p(cash)$ and $p(cashless)$. An agent caught evading a transaction gets a fine equal to F_1. If agents pay in cash an amount greater than the cash threshold L, they pay a sanction equal to F_2, if they are caught. Let A be the face value of the transaction, τ the tax rate and I the indicator function. In such a simple framework the payoffs of the evaders are:

$$V_{E,cash} = -[F_1 + F_2 I(A > L)]p(cash) - c_{cash}, \tag{P1}$$

$$V_{E,cashless} = -F_1 p(cashless) - c_{cashless}, \tag{P2}$$

while the payoffs for compliers are:

$$V_{C,cash} = -(\tau A + c_{cash}) - \infty I(A > L), \tag{P3}$$

$$V_{C,cashless} = -\tau A - c_{cashless}, \tag{P4}$$

where c_{cash} and $c_{cashless}$ are respectively the costs associated with the use of cash and cashless payment instruments. Given that compliers always stick to the rules, the cost of exceeding the threshold L is equal to infinity.

It follows that if cash is fully anonymous, $p(cash) = 0$, as often assumed in the literature (see Garratt and van Oordt, 2021, among others), evader's payment choice is never influenced by L, and L is only binding for compliers. On the other hand, the compliers just avoid to pay amounts that exceed L in cash.[19]

It is also easy to see that if (i) $p(cash) = 0$, $p(cashless) = 1$ and (ii) $c_{cashless} - c_{cash} < F_1$, evaders always pay with cash. Usually, F_1 is much higher than c_{cash} and $c_{cashless}$, so condition (ii) is very likely to be met.

In this simple economy the government has different tools to directly fight evasion: F_1, F_2, L, $p(cashless)$ and τ. It can also try to influence indirectly $c_{cashless}$ and c_{cash} subsidizing cashless payment or taxing or limiting cash (Gesell, 1916; Goodfriend, 2000; Buiter and Panigirtzoglou, 2003; Buiter, 2009; Mankiw et al., 2009; and Rogoff, 2014; Immordino and Russo, 2018a). Observe that changing $p(cashless)$ alters the relative privacy of cashless instrument with respect to cash. A second important observation is that all these parameters influence the demand for cash in such a framework. By influencing the payoffs of payments settled using cash vs cashless instruments, they have an impact on the balances needed for the relative transactions, i.e., cash inventory and deposits at commercial banks. Although they can be of practical relevance, we abstract from other mechanisms that are related to irrational behavior, law misunderstanding, political signaling or other sophisticated strategies that the tax revenue agency could implement in parallel. This simple model is useful just as a guide for interpretation, it is not an exhaustive framework for tax evasion and payment choices. Even though some variables are fixed and exogenous, the model can describe the main mechanisms we are interested in without superfluous complications and formulate explicit and simple hypotheses to test empirically.

[17] For simplicity, we assume that every transaction is always between the same types of agents. See Fedeli and Forte (1999), Chang and Lai (2004) and Marceau and Mongrain (2002) for models of bilateral tax evasion, with agent decision to evade or comply potentially endogenous. For our simple framework, we do not strictly need these assumptions, but they make things easier.

[18] For simplicity, we abstract from other methods that can be used to hide taxable transactions like cryptocurrencies, transactions from shell business entities in offshore financial services, inflated invoices, personal services, and so on.

[19] $p(cash) = 0$ is a standard assumption in the literature on money and privacy (see Garratt and van Oordt, 2021, for example). However, the still ongoing debate on cash thresholds in Italy and elsewhere and the fact that other studies that analyze the effects of these thresholds on evasion do not make this assumption (see Russo, 2022 and Giammatteo et al., 2022) proves the need to explicitly formulate it.

3.2. Hypotheses on the effects of cash thresholds and accessing bank data

To stick with our main empirical questions, our focus is on the effects of accessing bank data (setting $p(cashless) = 1$, as happened in Italy in 2015), and then increasing cash thresholds (increasing L, as happened in Italy in 2016). From this simple model, it is easy to see that both L and $p(cashless)$ affect positively the demand for cash, though through different mechanisms. Under the assumptions made, increasing L, affects positively only the compliers' demand; while setting $p(cashless) = 1$ affects positively only evaders' demand.[20] Under the assumptions outlined above, we can formulate the following hypotheses to test empirically:

H1. Accessing bank data, i.e. setting $p(cashless) = 1$, increases the demand for cash.

H2. Under bank data visibility, increasing cash thresholds, L, has a positive effect on the demand for cash.

H3. If *H1* holds true, the increase in cash demand triggered by accessing bank data is mainly driven by evaders.

H4. Under bank data visibility, if *H2* holds true, the increase in cash demand triggered by higher cash thresholds is not mainly driven by evaders.

4. The effects of bank data visibility and cash thresholds on the demand for cash

In this section, we introduce our empirical strategy and main measurement, and test *H1* and *H2* using low and high frequency methods.

4.1. Empirical strategy

Our empirical analysis is structured as follows. We first include the change in bank data visibility in 2015 and cash thresholds in 2016 in a simple cash demand equation with monthly data. Secondly, we use high frequency (daily) data to analyze the reaction of cash demand to the policies around the exact implementation dates. This gives us sharp identification of the effects of the policies because we use narrow time intervals, in which other relevant factors for the demand for cash (like those we listed in Section A.2 of the online appendix) are constant. In both analyses, we exploit data on the demand for different denominations (as in Kohli, 1988), which also helps to assess whether the aggregate demand is driven by transactions or store-of-value purposes.

4.2. Measurement of cash demand

The main dependent variable in our study is the value of net cash withdrawals of commercial banks from central bank branches. The public can obtain additional currency only against deposits at commercial banks, using the ATM or at the bank teller. In turn, the only way commercial banks can obtain banknotes is from the central bank. It follows that, by subtracting the amount of cash returned to that withdrawn, we can approximate the variation of cash holdings of all bank's depositors with these operations. A nice feature of this data is that it reconstructs exactly the aggregate numbers of cash issued by the central bank and not just a sample. Under stable supply of banknotes from the borders and without hoarding by commercial banks, this measure provides a reliable, timely and high frequency indicator of the demand for cash by the public.[21] We focus on the period between January 1st, 2010 and March 31st, 2018. In Section A.1 of the online appendix, we provide evidence on the robustness of our main assumptions. Figure A.1.1 shows that Italian banks, despite the negative interest rates applied on the deposit facility from 2014, did not hoard cash.[22] In order to keep their caveau flat, Italian banks actively managed their cash holdings, returning the notes in excess or withdrawing when depositors demand increased. As Italy is part of a monetary union, the additional demand for banknotes can also be satisfied by cross-border shipments. In particular, given that Italy is a major touristic destination, people from other euro countries can bring banknotes to spend them during their journey. Figure A.1.2 in the online appendix shows why this aspect is not problematic in our analysis. Indeed, the tourists' flow

[20] As cashless balances are observable as well (as a sum of cashless transactions) and evaders can hide wealth there, p(cashless) also impacts the store-of-value demand for cash, in addition to transactions demand.

[21] The net withdrawals reflect the change instead of the level of cash in circulation. We prefer this specification to the level for several reasons. First, given that the initial point of the stock of banknotes at the disaggregated level is unknown, we cannot use meaningful series for the level. Second, the change is not persistent as the level and thus it is easier to include simple policy dummies in the model and endogeneity issues are less relevant. Third, cash demand is often in non-linear relationships with other variables, like the interest rate, using its first differences allows us to use a simple linear model. Some papers use gross deposits and gross withdrawals or the sum of them (see Ardizzi et al., 2014a, 2018 and Giammatteo et. al., 2022), from low frequency data on banks' cash deposits or anti-money laundering reports of transactions above 15,000. Such an approach can be useful to analyze money laundering activity, but it does not allow to fully reconstruct cash holdings and usage, also because the 15,000 threshold is too high. In addition, it is low frequency data and thus it does not allow sharp identification of policies' effects, as we show below. Instead, our measure can track all cash holdings effectively on a daily basis. Furthermore, according to the Tobin-Baumol model, any increase in cash usage and disbursements (T in Baumol, 1952) due to higher cash thresholds for example, induces higher cash inventories, which are detected effectively by net cash withdrawals.

[22] In other countries, like Germany, banks did it, see the "The demand for euro banknotes at the Bundesbank" in the Monthly Report of March 2018.

did not change dramatically in correspondence of the implementation of the policies under analysis. Figure A.1.3 depicts the time series of cumulated monthly net cash withdrawals of commercial banks over the considered period. Its visual inspection signals a change in the currency in circulation in 2015 and 2016, which may be connected to changes in bank data visibility and cash thresholds. Cash demand can be measured in alternative ways, like household survey and payment diary data or supervisory reports,[23] but these measures have low frequency and not exact information on the denomination of banknotes and do not precisely reconstruct cash holdings, three key dimensions to identify the effects that we are interested in.

4.3. Baseline results

In our preliminary analysis, we model cash demand with a simple linear specification:

$$b_{t,d} = \varphi_d F_t + \rho_d L_t + \beta_d x_t + \varepsilon_{t,d}, \tag{1}$$

where $b_{t,d}$ represents the demand for banknote denomination d at month t, F_t is a dummy variable whose value switches to one when bank data is made visible in January 2015, L_t is a dummy variable whose value becomes one when the cash threshold is increased from 1,000 to 3,000 euro in January 2016, $\varepsilon_{t,d}$ is a normally distributed error with average zero and unknown variance. Based on our review of the main drivers for cash demand in Section A.2 of the online appendix,[24] we set $x_t = [C_t, I_t\ r_t, PD_t, B_t, m_t\ ]$, where C_t is final consumption expenditure of domestic households at current prices, which also captures inflation effects, I_t is the value of payments made through instruments different from cash (credit transfers, direct debits, cards, cheques),[25] r_t is the average rate applied to bank deposits in Italy, PD_t is the average of daily returns of FTSE Italia All-share Banks Index, B_t is the average spread between 10-year BTP and Bund, and m_t is a set of controls for seasonal effects (month dummy variables). All variables are computed with monthly frequency.[26] A detailed description of these variables is provided in Section A.2 of the online appendix. Table 1 displays the OLS estimates of φ_d and ρ_d in model (1). 500, 200 and 100 euro banknotes denominations are taken into account individually, while smaller denominations (lower than 100 euro) are aggregated for convenience.[27]

Table 1 shows three interesting pieces of evidence. First, making bank data visible seems to have significantly contributed to increase the demand for highest denomination banknotes, i.e. 500 and 200 euro, the most efficient banknotes to store (and hide) value. Second, the increase of the change in the cash threshold from 1,000 to 3,000 euro seems to have increased significantly the demand for 100 and 200 euro, which are the most efficient banknotes to settle transactions with amounts included between the former and the current threshold. Third, the demand for denominations lower than 100 euro does not seem to be influenced by the policies at all. The total impact of these two policies is significant, amounting to more than 1.5 percent of the GDP and more than 2 percent of banks retail deposits.[28]

The parameters of interest in our analysis, φ_d and ρ_d in model (1), are identified under the following assumptions: (A1) there are no variables impacting cash demand and correlated with F_t and L_t that are omitted; (A2.1) both the policies did not react to short term changes of cash in circulation or (A2.2) each policy did not react to short term variation of cash and they are independent from the other regressors. Assumption (A2.1) holds under the following specific hypotheses in our case: (a) cash thresholds do not change monthly as a function of cash in circulation; (b) monthly variation of cash in circulation does not influence fiscal authority regulation; (c) the central bank does not determine official rates based on the variations of cash in circulation; (d) financial markets do not factor the variations of cash in circulation in banking sector risk and country risk; (e) the value of payments settled with credit transfers, direct debits, cards, cheques does not depend on cash in circulation; (f) consumption expenditure do not vary depending on banknotes held by consumers.

Even though these assumptions seem plausible (probably except for (e)), we cannot be sure that some relevant variable is omitted and (a)-(f) hold or that F_t and L_t are fully independent from other regressors and (a)-(b) hold. The combination of A1 and A2.2 seems plausible if we believe that these policies were not influenced by the other factors included in the model and did not happen simul-

[23] The Survey of Consumer Payment Choice (SCPC) in US is an example, see Schuh and Stavins (2010) for a description. Survey data can be useful to detect heterogeneity in cash demand by taxpayers' type, for example Russo (2022) uses data from the survey on household income and wealth data of the Bank of Italy to study different cash expenditure between employees and self-employed. See Bagnall et al. (2014) for a cross-country comparison of results from payment diaries. Banks could report cash operations at ATM or anti-money laundering information.

[24] Out of the drivers for cash demand outlined in Section A.2 of the online appendix, the only one that is not included in the model is the shadow economy. The exclusion is motivated by: (i) data being available only from 2011 to 2016, while the period of our analysis is more extended (January 2010 – March 2018); (ii) data being produced only with annual frequency (just 6 data points available). Even with this limited information available, the trend observed for the shadow economy (growing from 2011 to 2014, decreasing in 2015 and increasing again in 2016) does not seem correlated with the one of cash demand in Italy (see Appendix A, Figure A.1.3).

[25] This regressor is likely to be endogenous, but here we are not interested in estimating its causal effect on the dependent variable, instead we just want to control for its level, thus we avoid the use of instrumental variables. Instead, we exploit high frequency data for stronger identification in Section 4.4.

[26] Consumption and use of cashless instruments are only available quarterly, we keep them constant during the quarter's months and set them equal to the difference between the current and the previous quarter values.

[27] In Italy the maximum denomination available at the ATM is 50 euro. Banknotes smaller than and equal to 50 are easily available and used for common transactions. This threshold may vary across euro countries.

[28] The impacts are estimated as the difference between the expected value of net cash withdrawals in the presence of the policies effect and without them using model (1).

Table 1
Baseline results of the econometric analysis
Demand by banknote denomination.

Dependent variable: monthly net cash withdrawals in euro				
Banknote denomination	<100	100	200	500
Access to bank data	80,133,463	128,834,444	24,198,696 **	228,665,183 **
	(296,682,008)	(103,556,374)	(10,221,042)	(99,752,509)
Higher cash thresholds	188,305,402	274,061,642 ***	55,811,905 ***	131,812,603
	(301,429,544)	(105,213,493)	(10,384,601)	(101,348,758)
R^2	0.94	0.62	0.60	0.41
N. Obs	99	99	99	99
Month fixed effects	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes
Time varying controls	Yes	Yes	Yes	Yes

Notes: *=p<0.1; **=p < 0.05; ***=p < 0.01. Period: January 2010 - March 2018. The dependent variable is the value of net cash withdrawals of commercial banks from central bank branches expressed in euro. "Access to bank data" and "Higher cash thresholds" are dummies that switch to one when the policy enters into force. Standard errors in brackets. Time varying controls are described in Section A.2 of the online appendix.

taneously with unobservable ones. Section B.1 of the online appendix evaluates the possible persistence and simultaneity of the residuals. In Section B.2 of the online appendix, the hypothesis of a non-linear impact of the considered policies on the demand for cash is taken into consideration. In Section B.4 of the online appendix, we provide evidence on the exogeneity of the policy dummies to monthly net cash withdrawals. Observe that, given that the cash threshold changed after the access to bank data, its coefficient captures the interaction of the two policies. In Section B.5 of the online appendix, we consider also changes of cash thresholds that took place before bank data was made visible and of opposite direction (decreasing cash thresholds). The effects on cash demand are largely confirmed.

4.4. *High frequency analysis*

Taking advantage of daily data, the purpose of this analysis is to verify whether the change in the public's preferences for cash holdings occurred precisely at the entry into force of the policies. If this is the case, we only need to assume that in the same day, and not in years, other confounding factors did not affect cash demand in order to identify the effects of the policies. This gives us sharp identification of the effects of the policies because other relevant and potentially unobservable factors of the demand for cash are constant in narrow intervals around the implementation dates. To clean our data from systematic patterns in the daily series of cash net withdrawals, we construct a time series of "unexpected net withdrawals" by denomination:

$$d_{t,d} = b_{t,d} - \widehat{\beta_d} w_t,$$

where the subscript d indicates the denomination, t the day, $b_{t,d}$ is the value of net cash withdrawals for denomination d in day t, w_t is the th row of the matrix $W = [M,S,C,C_I,C_P,E,E_P,F,F_I,F_P,M_I,M_F]$, which includes a wide set of controls that captures the daily features of net cash withdrawals.[29] As we want to exploit high frequency data, we do not include controls listed in Section A.2 of the online appendix, which have mostly lower frequency. This choice should not create concerns because low frequency factors have also high persistence and do not change suddenly from one day to the next, unless some huge structural break occurs.[30] A visual inspection of unexpected net withdrawals for different denominations at high frequency is provided in Figure A.3.1 of the online appendix. In what follows, we let the data tell us when the policies impacted cash holdings using endogenous structural break tests, which estimate break dates close, if not coincident, with the implementation dates.

Two econometric tests are used to identify policy-induced breaks in the time series and confirm the effects of the policies identified

[29] This is an important step to do with daily data on cash operations because there are specific patterns to control for, in order to compare cleanly different days. For example, net withdrawals are structurally higher on Fridays or before Christmas, because people get more cash for purchases. M are monthly dummies (January is omitted), S are daily dummies (Monday is omitted), C are dummies that have value 1 in the broader Christmas period (December 20-January 6), C_i are dummies that have value 1 in the narrower Christmas period (December 23 – January 1), C_p are dummies that have value 1 in the period after Christmas (January 7 – January 15), E are dummies that have value 1 in the Easter period (depending on the year), E_p are dummies that have value 1 in the period after Easter (depending on the year), F are dummies that have value 1 in the broader period of summer vacations (August 1 – August 20), F_i are dummies that have value 1 in the narrower period of summer holidays (August 12 –August 17), F_p are dummies that have value 1 in the period after the summer (August 21 – August 31), M_I are dummies that have value 1 at the beginning of the month (1 - 5), M_F are dummies that have value 1 at the end of the month (25 - 31). $\widehat{\beta_d}$ is derived from simple OLS estimation of $b_{t,d} = \beta_d w_t + \varepsilon_{t,d}$.

[30] From this perspective, the analysis draws from event-study analyses of unexpected returns and flows (see Dodd and Warner, 1983, among others), but focuses on different tests. Apart from the difference in the phenomena under investigation, from a statistical point of view the main difference is that we do not have many events concerning different firms, (like in Del Guercio and Tkac, 2008, for example). For this reason, our analysis does not follow exactly an event-study approach but it uses some useful concepts.

as significant in Table 1. The first one is the Chow (1960) test, by which we test the hypothesis of invariance of the parameters of a linear regression during a given period. Specifically, a date in which a structural break has potentially occurred is selected *ex-ante*, and the constancy of the coefficients before and after the considered date is tested. In practice, the test is made on the constant term of the unexpected net withdrawals (d_t). The Chow test on the implementation dates always signals a break in the policy implementation dates, except for the effect of accessing bank data on 200 euro. To further assess the robustness of these results, we explore the response that the Chow test would give if the exogenous break date were changed. The test is applied to each day in a period ranging from 50 days before to 50 days after the entry into force of the policies on 500, 200 and 100 euro banknotes demand.[31] The test reaches its maximum exactly or few days around the policy implementation date (see Figure A.3.2 in the online appendix). In three out of four cases (excluding 200 euro for the bank data visibility) the statistic reaches the maximum value around the date of entry into force of the policy.

Given that the Chow test takes the break date as given, the results are influenced by the econometrician's choice. To be more confident on our findings we also use the test proposed by Bai and Perron (2003) to identify potential structural break dates (endogenous breakpoints), that are not selected *ex-ante*, but inferred from the time series itself. Fig. 1 represents the cumulated unexpected net withdrawals for 500, 200 and 100 euro in a range of 100 days around the date of implementation of bank data visibility in 2015 (panel (a)) and the cash threshold increase in 2016 (panel (b)), the vertical dotted line represents the estimated break point, and the red horizontal line depicts the 95 percent confidence interval. We can see that the policy implementation date (day 50) is always in the interval and that the estimated break point is always coincident or very close to it, apart from the effect of bank data visibility on 200 euro. We then discard the effect of this policy on 200 euro. In Section B.2 of the online appendix, where we also check for possible non-linear effects, that could be neglected here, we find confirmation of the insignificance of this effect (see the center panel of Table B.2.1). In Section B.3 of the online appendix, we use a different time range (300 days) for both the structural break tests, the results remain unchanged. It follows that we can only find robust evidence on the effect of the bank data visibility on the highest denomination (500).

The results in this section bring reassuring evidence against potential endogeneity issues. First, the sudden breaks estimated in correspondence of the implementation dates confirm that the increased demand for cash is imputable to tax evasion policies and not to other unobservable factors. Indeed, most of the other drivers (see Section A.2 of the online appendix) are persistent processes, which are not likely to change from one day to the next. This is reinforced by our evidence on banknotes denominations. The demand for 100 and 200 reacts to payments threshold change from 1,000 to 3,000, while 500 to deposits monitoring and the other notes do not present breaks at all. For example, a break in cashless services provision, shadow economy or consumption should manifest in all denominations. Second, we showed how the implementation of the policies has an instantaneous and strong impact on the demand for cash (driven by the fear of direct and immediate punishment), while these policies are not triggered by short-term variation of cash in circulation (see Section B.4 of the online appendix). In other words, our identification rests on not synchronous potential causality of the dependent and the explanatory variables and high frequency measurement.

5. Effects on regions with heterogeneous tax evasion propensity

After having secured enough evidence on *H1* and *H2*, we test *H3* and *H4*. Given that we cannot observe cash demand and tax evasion at the individual economic agent level, we exploit variation across Italian regions in terms of tax evasion propensity to see whether changes in bank data visibility and cash thresholds had a higher impact on cash demand in regions with higher or lower propensity to evade taxes. Finding higher effects in regions where tax evasion is higher (lower) would support the idea that higher cash demand following policy implementation is driven by evaders' (compliers') behavior.

Measures of tax evasion are notoriously imprecise, because of its intrinsic opacity. There are several ways to approximate tax evasion propensity and a long debate has been opened about how to measure unreported, non-observed, underground, illegal, informal, shadow, and unrecorded economies.[32] Our goal here is not to contribute to this debate, but to find a reliable approximation that captures the main differences between Italian regions. A way to approximate tax evasion propensity is through the non-observed economy, for which an estimate at the regional level for the period under analysis is produced and used by reliable institutions in Italy, oppositely to other measurements. In addition, considering the non-observed economy allows us to capture cash demand of agents operating in the illegal and informal economies among the others (see the examples in Section A of the online appendix). We use the measure produced by the national institute of statistics (ISTAT): the estimated value added produced by the underground, the informal

[31] The choice of the temporal range is arbitrary. In Section B.3 of the online appendix the results relating to the period from 150 days before to 150 days after are also reported. They confirm the main evidence.

[32] A non-exhaustive list includes Feige, (1979; 1980;1989), Schneider et al. (2010a; 2010b; 2010c; 2011); Buehn & Schneider (2012a); Schneider & Williams (2013); Schneider & Enste, (2013).

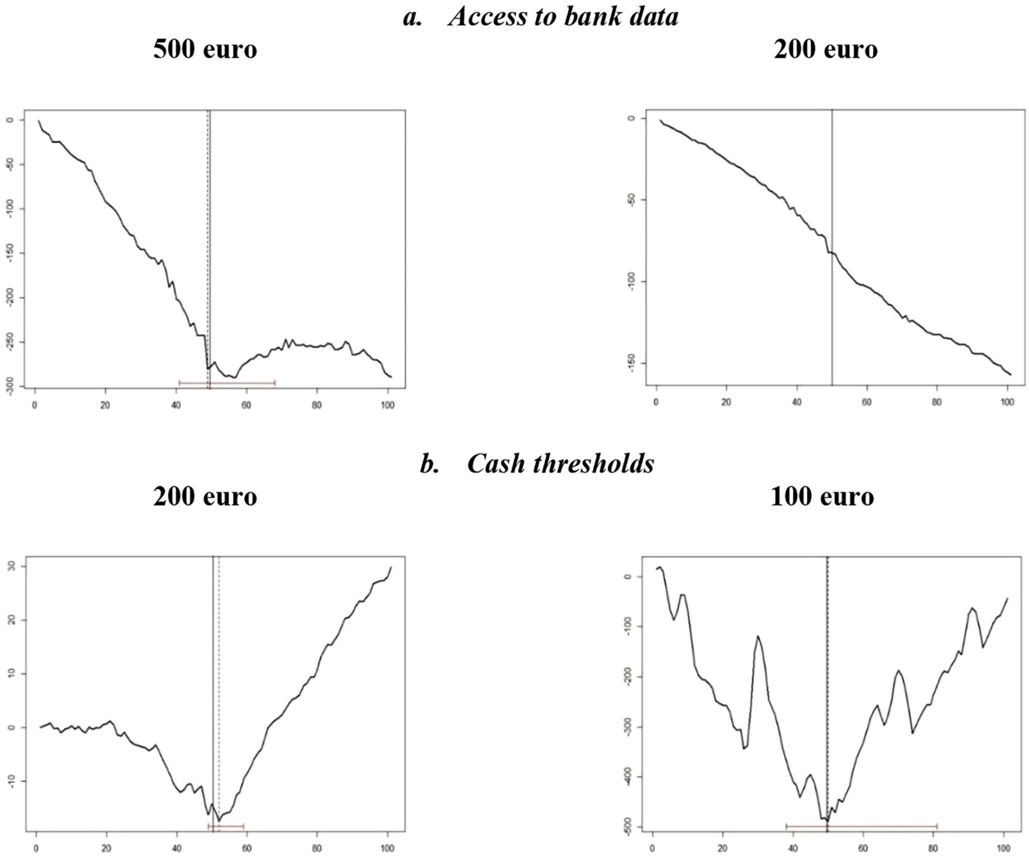

Fig. 1. Endogenous breakpoints test
Notes: x-axis: 100 days around the implementation date (50th observation). Y-axis: cumulated daily net withdrawals in the time interval, expressed in million euro. The solid vertical line is the policy implementation date. The dotted vertical line is drawn at the break date identified by the Bai and Perron algorithm. The horizontal line is the confidence interval at 95 percent.

and the illegal economy.[33] It consists of the amount of unobserved value added resulting from misrepresentations regarding turnover and/or costs, or the use of non-regular labor inputs. With respect to the under-reported value added generated by irregular labor inputs, the value of the related value-added tax due but not paid to the Treasury (VAT fraud) is also included. All these features make the non-observed economy particularly appropriate for our purposes, as agents within these economies can use cash to hide wealth and transactions.

Let us start by describing tax evasion heterogeneity across Italian regions in Table 2. As the non-observed economy depends on the

[33] The ISTAT measure is quite standard if compared to those produced by other national statistics institutes. We briefly provide some details here, see this link (only in Italian) for more details. In addition to the statistical underground, due to information inefficiencies (sampling and non-sampling errors) or coverage errors in the archives, the underground economy includes all activities voluntarily concealed from tax and social security authorities. The illegal economy includes activities that produce illegal goods and services, or that, while involving legal goods and services, are carried out without proper authorization or title. The informal economy includes all productive activities carried out in little or no organized settings, based on labor relations not regulated by formal contracts. The illegal economy is limited to the definition adopted by ESA 2010. It is worth remarking that, differently to international studies, here we are comparing regions within the same nation, thus distortions due to cross-border differences in measurement or institutions are not in place here.

size of the economy, we divide it by the regional GDP.[34] There is substantial heterogeneity across Italian regions, evasion rates range from 8 to 24 percent. The northern regions present a lower evasion rate on average, and southern regions are characterized by the highest. Although northern regions are also richer, the ratio between the non-observed economy and GDP does not necessarily capture economic development, as shown in Figure A.4.1 in the online appendix, where it is plotted against the regional GDP. Given that our measure of cash demand is at the central bank branch level, and there is at least a branch in every region, we can match our data with regional tax evasion information.[35]

If the additional demand for cash triggered by changes in bank data visibility and cash thresholds is associated to tax evasion, we should observe a higher demand from regions where evasion is higher, *ceteris paribus*. In Fig. 2, we provide some visual evidence on the behavior of cash holdings around the policies implementation dates. We consider three regions: Calabria, the southern region that presents the highest incidence of the non-observed economy on average; Trentino-Alto Adige, the northern region that has the lowest incidence; and Marche, a central region that is equally distant from both these extremes. We exploit the high frequency of our data and plot the daily seasonally adjusted regional net cash withdrawals of 500 euro for bank data visibility in panel a) and the sum of 100 and 200 euro for cash thresholds in panel b). The figure shows similar decreasing trends across all the regions before both policies. Interestingly, making bank data visible induces a trend inversion in Calabria, the highest tax evasion region, and no change in Trentino-Alto Adige, the most tax compliant region. On the contrary, higher cash thresholds trigger a remarkable increase in Trentino and a significant one in Marche but it does not affect the demand in Calabria at all. Similar results are obtained considering other regions along the tax evasion spectrum. To test more formally our hypothesis, we consider all the Italian regions and estimate the following model:

$$\widetilde{b}_{t,r} = \gamma_0(P_t = 0) + \gamma_1(P_t = 1) + \mu T_r + \tau P_t T_r + \varepsilon_{t,r}, \tag{3}$$

where $\widetilde{b}_{t,r} = b_{t,r}/gdp_{t,r}$ represents the demand for cash in region r a day t over the regional GDP. P_t is a dummy variable whose value switches to one when the policy enters into force, T_r is a variable that captures the *ex-ante* propensity to evade of taxpayers in region r, the non-observed economy over the regional GDP observed in the year before the policy enters into force, γ_0 and γ_1 capture all the factors affecting respectively the pre and post policy period, $\varepsilon_{t,r}$ is a normally distributed error with average zero and unknown variance.[36] The high frequency of the data helps us to tackle the potential omitted variable problem again. We take very narrow time intervals of 60, 70 and 80 calendar days around the policies' implementation dates in which we can assume that region-specific unobserved factors are constant. In this way the parameter τ captures the change in cash demand only due to the policy.[37] We run different regressions for the two policies. Based on the evidence in the previous section, we focus on a time interval around the policy implementation and on the demand for 100 and 200 banknotes for the cash threshold policy and the demand for 500 for the deposits monitoring policy. Table 3 shows the estimated coefficients of model (3) using 60, 70 and 80 calendar days around the policies' implementation dates, respectively in columns (1), (2) and (3). From the first panel of the table, we can see that tax evasion has a positive effect on the demand for 500, and τ, the interaction term, is significant. This means that when bank data was made visible, the high-tax evasion regions converted more deposits into cash w.r.t. to the low-tax evasion regions. From the second panel of the table, we can see that a higher cash threshold does not have a higher effect in regions with higher tax evasion.

From this regional analysis it seems that the bank data visibility has a higher impact on regions with a higher share of the non-observed economy. An increase of ten percentage points of the non-observed economy implies an increase of 3 percentage points of net withdrawals over GDP during a year without bank data visibility, against 5.5 percentage points with it. The interaction with higher cash thresholds has the opposite sign but the standard errors are quite high. This evidence can be rationalized by our conceptual framework in Section 3, assume:

$$c_{cashless} = c_{cash} = 0 \quad (S1) \quad \text{and} \quad p(cash) = \alpha < F_1/(F_1 + F_2) \quad (S2)$$

and focus on the tax evaders payoffs (*P1*) – (*P2*). Assuming (*S1*) (i.e. that the costs for cash and cashless payments is equal to zero) is a simplification, but it is not implausible because they are generally very small with respect to F_1 and F_2 and it eases the illustration. Setting them small enough does not change the following analysis. Assumption (*S2*) implies $F_1(1-\alpha) > F_2\alpha$, that means that the

[34] The non-observed economy (as other measures) could be higher in traditional organized crime regions and could, but this not necessarily. For example, Umbria and Sardinia have a high non-observed economy, but are not organized crime regions, like Campania or Sicilia.

[35] Commercial banks withdraw and deposit cash at the regional branches of the central bank. We compute the net withdrawals at the regional level. Even though a commercial bank can withdraw systematically in one region and deposit in another one, such structural difference in flows of banknotes should not change in correspondence of the policies for reasons correlated to them. Identification issues may arise if a commercial bank changes suddenly its logistics exactly in correspondence of the policy. We do not find any evidence of such an event in our sample period, which is particularly narrow as we use less than 100 days around the policies implementation. The inspection of regional net withdrawals reveals that most of the regional time series have a behavior close to the national one, which indicates a small likelihood of encountering systematic cross-regional patterns in the period we are investigating. We cannot report the regional breakdown for confidentiality issues.

[36] A higher frequency variable of regional tax evasion does not exist, so we cannot include region fixed effects in the regression. This implies that μ may also capture the heterogeneity of regional characteristics that are correlated with tax evasion.

[37] In this way, to identify τ we only have to assume that there are no time-varying region-specific unobserved factors that change in the very same date of the policy's implementation. This is the best we can do because we cannot use region fixed effects, as we do not have high frequency data on tax evasion, which we are not even aware of.

Table 2
Non-observed economy over regional GDP.

Region	2011	2012	2013	2014	2015	2016
Abruzzo	0.153	0.152	0.159	0.157	0.201	0.191
Basilicata	0.128	0.139	0.142	0.150	0.179	0.174
Calabria	0.228	0.224	0.226	0.230	0.247	0.242
Campania	0.221	0.213	0.208	0.215	0.234	0.232
Emilia Romagna	0.091	0.093	0.097	0.100	0.144	0.141
Friuli-Venezia Giulia	0.095	0.099	0.100	0.108	0.137	0.133
Lazio	0.138	0.138	0.149	0.161	0.154	0.154
Liguria	0.105	0.111	0.115	0.121	0.158	0.159
Lombardia	0.091	0.095	0.095	0.102	0.127	0.125
Marche	0.087	0.089	0.094	0.102	0.180	0.178
Molise	0.145	0.150	0.149	0.156	0.206	0.204
Piemonte	0.093	0.104	0.107	0.110	0.144	0.144
Puglia	0.173	0.171	0.165	0.168	0.222	0.220
Sardegna	0.140	0.141	0.143	0.148	0.200	0.203
Sicilia	0.194	0.195	0.198	0.203	0.223	0.222
Toscana	0.097	0.101	0.106	0.111	0.172	0.171
Trentino-Alto Adige	0.080	0.091	0.094	0.096	0.130	0.127
Umbria	0.118	0.125	0.128	0.125	0.198	0.195
Valle d'Aosta	0.079	0.092	0.098	0.099	0.158	0.155
Veneto	0.082	0.083	0.083	0.088	0.143	0.138

Source: Confcommercio and CGIA Mestre elaboration on ISTAT data. Note: Confcommercio estimates the incidence of the non-observed economy on GDP; CGIA Mestre, starting from the the non-observed economy/GDP incidence, estimates the actual evasion percentage at regional level. Confcommercio data is available from 2011 to 2014, CGIA Mestre from 2015 to 2016. Even if the average level changes over time because of different computation methods, the two different series present a similar ranking over time and do not pose issues in cross-sectional comparisons.

evasion fine times the probability of not observing a cash transaction is bigger than the fine for exceeding the cash threshold times the probability of observing a cash transaction. Given that usually $F_1 \gg F_2$, i.e. evasion is punished more severely than exceeding cash thresholds, $F_1/(F_1 + F_2)$ is not a strict and unrealistic upper bound for α, the probability of being observed in a cash transaction, which in practice is very small, and often assumed equal to zero (see Garratt and van Oordt, 2021, among others) and surely smaller than its complement $1 - \alpha$. The upper panel of Table 4 reports the payoffs under assumptions (S1)-(S2) when the payment amount is lower than the threshold, the lower panel reports the payoffs when the amount is higher. Accessing bank data (in this simple setting increasing $p(cashless)$ from α to 1) always makes cash strictly preferable to cashless instruments, as $F_1\alpha < (F_1 + F_2)\alpha < F_1$. Increasing the threshold L when $p(cashless) = 1$ does not change the evaders' demand for cash because they prefer it, whatever the threshold is. The threshold can change evaders' demand for cash only if bank data is not visible, in our simple example when $p(cashless) = p(cash) = \alpha$, in line with the empirical evidence in Russo (2022).[38] Nevertheless, $p(cashless)$ may be significantly greater than $p(cash)$, as electronic transactions always leave footprints in payment systems and banks' books and keep evaders away from cashless instruments even without full visibility.

To provide more evidence we can look at regional tax revenues before and after the implementation of the policies and see whether they changed differently in regions where cash demand changed more dramatically after the policies. Limitations encountered in this type of analysis are that data on tax revenues (ii) is not available at the regional level, and (ii) is not frequent (at best yearly). We compute the share of GDP generating tax revenues by subtracting the non-observed economy to the regional GDP and divide this number by the GDP.[39] If more cash is used to evade taxes in a region after the policy, the share of regional GDP which taxes are paid on should decrease, *ceteris paribus*. We estimate the following model:

$$r_{y,r} = \theta\widetilde{b}_{y,r} + \varphi F_y\widetilde{b}_{y,r} + \rho L_y\widetilde{b}_{y,r} + \mu_y + \mu_r + \varepsilon_{y,r}, \tag{4}$$

where $r_{y,r}$ is the share of GDP generating tax revenues during year y in region r. $\widetilde{b}_{y,r}$ is the amount of net cash withdrawals of 100, 200 and 500 banknotes over the GDP during year y in region r. F_y and L_y are two dummies that indicate respectively the year in which

[38] Russo (2022) shows that the reduction of payment thresholds in 2011 in Italy, before deposits monitoring was implemented, decreased cash expenditures more for self-employed households.

[39] This measure captures variations of tax revenues, under the assumption that the average tax rate is constant across regions. While cash demand is used to estimate national tax evasion, regional cash demand is not used to estimate regional tax evasion. The regional estimate considers other variables as regional not observed economy and effective tax rate at country-level. For this reason, there is no endogeneity-by-construction issue here. The use of time fixed effects controls for the use of cash demand at the aggregate level.

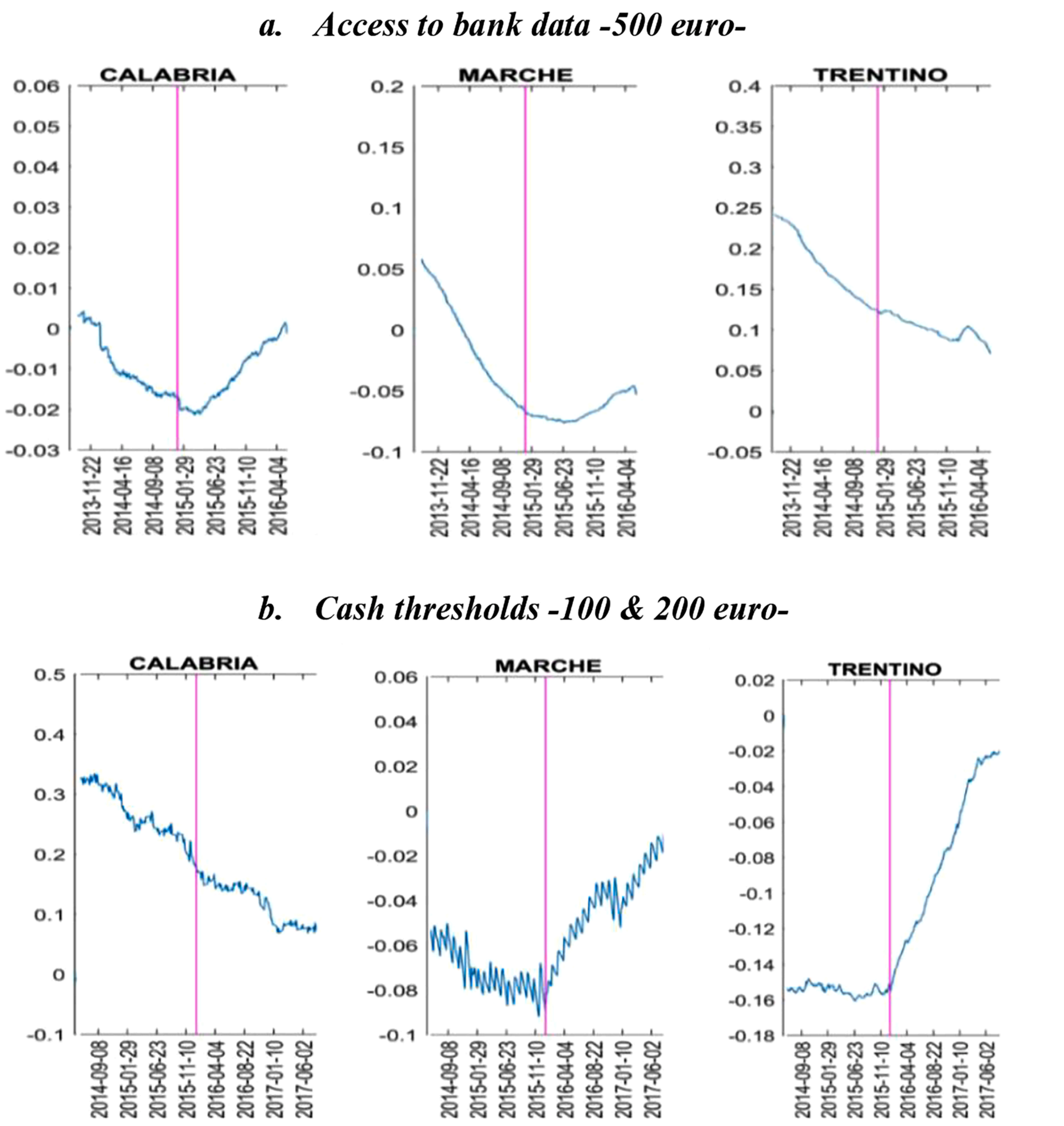

Fig. 2. Regional net cash withdrawals before and after the policies
Notes: x-axis: 100 days around the implementation date. Y-axis: daily seasonally adjusted regional net cash withdrawals cumulated from January 2010, expressed in million euro. The solid vertical line is the policy implementation date.

deposits monitoring and higher payment thresholds were introduced, μ_y and μ_r are respectively year and region fixed effects.[40] The first set of fixed effects capture year-specific changes in tax nation-wide revenues, including changes in the tax system and macro shocks. The inclusion of these fixed effects is key here because they capture also nation-wide policies. If for example tax revenues drive tax evasion policies, then there could be an endogeneity problem. Given that bank data visibility and cash thresholds are implemented

[40] We use time and space fixed effects as Giammatteo et al. (2022). Differently from their specification, our underground economy measure is more comprehensive (including both irregular work and undeclared value added), we have a wider time span and less granular geographical units (regions vs provinces), we include bank data visibility effects (while they have only cash thresholds effects), the variable interacted with the policy dummies is time varying and contemporaneous (while they use residuals from a 2010 regression on main determinants of their cash usage variable, which is the sum of withdrawals and deposits for anti-money laundering reported transaction above 15,000).

Table 3
Regional tax evasion and the demand for cash.

Access to bank data			
Dependent variable: regional 500 net withdrawals in euro			
	(1)	(2)	(3)
Tax evasion	0.0008 ***	0.0008 ***	0.0008 ***
	(0.0002)	(0.0001)	(0.0001)
Acces to bank data*Tax evasion	0.0007 ***	0.0006 ***	0.0006 ***
	(0.0002)	(0.0002)	(0.0002)
	Cash thresholds		
Dependent variable: regional 100 and 200 net withdrawals in euro			
	(1)	(2)	(3)
Tax evasion	0.0031 ***	0.0033 ***	0.0026 ***
	(0.0007)	(0.0006)	(0.0005)
Higher cash thresholds*Tax evasion	-0.0008	-0.0011	-0.0007
	(0.0010)	(0.0009)	(0.0008)
N obs	1,680	1,980	2,260
Calendar days around policy implementation	60	70	80
Pre and post policy dummies	Yes	Yes	Yes

Notes: *=p < 0.1; **=p < 0.05; ***=p < 0.01. Dependent variable: monthly net cash withdrawals at the regional level over regional GDP for all regions. "Higher cash thresholds" and "Access to bank data" are dummies that switch to one when the policy entres into force. "Tax evasion" is the *ex-ante* regional level incidence of Non-Observed Economy on GDP. Standard errors in brackets. The sample is constructed using the number of calendar days around the policy implementation is reported. The R^2 is around 0.10 for all the specifications. Standard errors in brackets. Pre and post policy dummies are two vectors assuming value equal to one for each day respectively before and after the policy implementation.

Table 4
Tax evaders' payoffs.

$A < L$		$p(cashless)$	
	V_E	α	1
payment choice	*cash*	$-F_1\alpha$	$-F_1\alpha$
	cashless	$-F_1\alpha$	$-F_1$

$A > L$		$p(cashless)$	
	V_E	α	1
payment choice	*cash*	$-(F_1 + F_2)\alpha$	$-(F_1 + F_2)\alpha$
	cashless	$-F_1\alpha$	$-F_1$

Notes: payoffs (V_E) of tax evaders derived in P1 and P2 of Section 3, under assumptions S1 and S2. F_1 is the tax evasion penalty, F_2 is the penalty for exceeding cash thresholds. $p(cashless)$ is the probability of observing a cashless transaction. A is the amount of the transaction, L is the cash threshold.

at the national level and not at the regional level, μ_y effectively control for this issue. The second set of fixed effects control for structural heterogeneity across regions, included tax compliance propensities. If higher demand for cash, triggered by the policies, is associated with lower (higher) tax revenues, φ and ρ should be significantly negative (positive). Table 5 reports the estimates for the first three parameters of model (4). In the first column, the sample includes years from 2014, in the second from 2013, and the third from 2012. On average, higher regional demand for cash is associated with lower tax revenues in all the three samples. However, significantly lower (or higher) tax revenue is not observed in regions with higher demand for cash when changes in bank data visibility and cash thresholds occurred.

Putting together these results with the others in the paper, it seems that both changes in bank data visibility and cash thresholds have a significant effect on the demand for cash. Making bank data visible generates a shift to cash balances mainly by evaders, who seek to preserve anonymity over their hidden transactions and wealth. Thresholds do affect the demand for cash as well, but it does not seem to be mostly driven by evaders, as they already prefer cash if bank data is visible. Nevertheless, these policies could have indirect effects on tax evasion generated by the implied higher cash in circulation (see Russo, 2022 and Giammatteo et al., 2022) or signaling effects on milder/tougher tax evasion tolerance, whose identification is challenging. Unfortunately, our data is not able to help identify cleanly the effect of these policies on tax revenues. If more granular data on tax payments and cash and cashless instruments usage were available, sharper results on the effects of these policies on tax revenues could have been obtained. We hope to see such type of

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