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Cash-Management in Times of Covid-19

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Abstract: The incidence of COVID-19 has systematically decreased households' use of cash as means of payment as well as the average size and frequency of cash withdrawals. We argue that the structure of Baumol–Tobin type inventory theoretical models and their extensions can be used to separate the confounding factors, such as the desired level of consumption and the choice of the fraction of consumption paid in cash, from the cash management behavior, i.e. the size and frequency of cash withdrawals. Using this insight we argue that the observed cash management is consistent with COVID-19 increasing the fixed cost of withdrawing cash. We use detailed data on ATM cash disbursements in Argentina, Chile, and the US to estimate how much the pandemic has changed the transaction cost of using cash. This estimation shows that if the intensity of the virus doubles in a county, cash transaction cost increases by approximately 2%. The results from Argentina, Chile, and the US are remarkably similar and robust to several forms of measurement error and endogeneity.

Keywords: COVID-19, cash, means of payments

JEL Classification Numbers: E4, E5

1 Summary and Introduction

The recent COVID-19 pandemic has altered households' use of cash in at least three important ways. First, as expenditures drop, households need less cash to pay for the same purchases. In the US, consumption expenditures dropped almost 9 percentage points from the first to the second quarter of 2020. Furthermore, lockdown policies implemented in many cities to combat the virus most affected the

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sectors of the economy that traditionally account for much of the cash exchanged in the US, like retail and restaurants.

Second, the risk and restrictions imposed during the pandemic has induced many consumers and businesses to embrace alternative payment methods. In particular, the higher volume of online purchases requires less cash to conduct these transactions. Furthermore, in the early stages of the pandemic, several central banks began disinfecting and quarantining paper money with the idea of stopping the spread of the virus. And, though the risk of infection from cash is now understood to be very low, these actions have prompted many brick and mortar establishments to either avoid using cash, or facilitate the use of other payments. Even the Centers for Disease Control and Prevention (CDC) recommended the use of touch-free payments whenever possible. In fact, in the Federal Reserve's May 2020 Diary of Consumer Payment Choice, 63% of respondents reported making no in-person payments in the first two months of the pandemic and 28% reported that they had been avoiding the use of cash.[1] Due to COVID-19, the *fraction* of total expenditures paid in cash has decreased.

Third, households' demand for cash has increased due to higher uncertainty. Indeed, the amount of currency in circulation in the US is at an all time high and increased more than 5 percentage points from the first to the second quarter of 2020. Respondents in the Diary of Consumer Payment Choice were carrying 17 percent more cash and had stored nearly twice as much cash elsewhere. Theoretically, there are several related channels from which higher uncertainty affects cash balances, starting from the option value emphasized in the seminal work by Miller and Orr (1966), as well as more recent contributions which emphasize uncertain expenditures such as Telyukova (2013) and Alvarez and Lippi (2013).

In this paper, we argue that the pandemic has affected households cash management practices through channels that are consistent with the structural properties of inventory theoretical models such as the classical Baumol (1952), Tobin (1956), or Miller and Orr (1966), or more recent versions of them such as Alvarez and Lippi (2009).[2] In particular, we argue that the observed cash management practices are consistent with a significant increase in the households' transaction cost of adjusting their cash balances, i.e. an increase in the ubiquitous "shoe leather cost" of obtaining cash from an ATM or from bank branches. Inventory theoretical models provide a way to "difference out" the overall decline in the volume of cash purchases from the cash-management decisions of households by combining the size and frequency of cash withdrawals. For instance, in the simplest case of the seminal Baumol–Tobin model, while decreases in the

1 Refer to Kim, Kumar, and O'Brien (2020) for details on the survey.

2 See Alvarez, Lippi, and Robatto (2019) for a survey of inventory theoretical models.

cash expenditures lead to lower average size and frequency of cash withdrawals, they do *not* change the ratio between these two statistics. Indeed, the ratio of the average withdrawal size to its frequency is independent of the desired expenditure paid in cash and only depends on the fixed cost of cash adjustments. A similar, slightly more complex argument holds for more general models.

Using this insight, we quantify the overall change in the cost of cash management during the COVID-19 pandemic using detailed data on ATM disbursements from Argentina, Chile, and the US. First, we find evidence that the cash-management behavior of households matches the predictions of the theory. We find evidence that in locations-periods with higher prevalence of COVID-19, while the average withdrawal size and frequency of withdrawals has decreased, there was an increase in the average size of withdrawals relative the number of withdrawals per unit of time. Using the logic of inventory theoretical models, we interpret this change as an increase in the transaction cost of adjusting a household's stock of cash. For instance, if the intensity of the virus doubles in a given county in a two-week period, the transaction costs of using cash increases by almost 2–3%. These estimates are remarkably similar across the three countries we study and robust after accounting for potential endogeneity and measurement error. Overall, we find that the cost of cash management has increased by approximately 1.5%.[3]

Our results indicate that the pandemic and ensuing lockdown policies have increase the cost of cash management. This increase in cost, together with the imperfect substitution across payment methods, implies that while the shift in payments to alternative methods has surely help households to cope with the effect of COVID-19, it is not without cost.[4]

2 Cash Management Models

In this section, we review a basic property of the classical Baumol–Tobin model and its generalization for extensions of this model. These are models of cash management which take as given a flow or stochastic process for cash expenditures. The key properties we want to summarize is how the observable quantities, such as the average frequency of withdrawals and its average size, depend on cash

3 This result is consistent with increased transaction costs in the corporate bond market (i.e. O'Hara and Zhou 2020; Kargar et al. 2020) during the COVID-19 pandemic. Traders have been forced to shift to slower agency trades as a result.

4 The welfare cost of inflation can be approximated as the area under the money-demand curve derived from the cash management models studied here. See Alvarez, Lippi, and Robatto (2019) and Lucas and Nicolini (2015) for more details.

expenditures and how these observable quantities relate to parameters of the model such as the "shoe leather cost", i.e. the cost of obtaining cash.

2.1 Baumol–Tobin

We let money M be an asset which pays no interest and assume that the rest of the assets pay the same nominal interest rate. The opportunity cost of holding money is therefore proportional to the nominal interest rate. Holding cash carries other opportunity costs as well, such as the probability of losing cash per unit of time. We denote R as the total opportunity cost of holding cash per unit of time. We assume that households spend C units of cash per unit of time; C is expressed in real terms. We emphasize that C is a flow per unit of time and it represents only cash expenditures.[5] Households can withdraw more cash by paying a fixed adjustment cost B, measured in real terms. B represents the transaction cost of "making trips to the bank" to adjust the stock of money, the ubiquitous shoe leather cost.

Households make N withdrawals of size W per unit of time. We impose the constraint that $W \times N = C$, meaning that households spend the cash they withdraw. We assume that the average cash balance is $M(W)$, and this function satisfies the following properties: (i) $0 \leq M(0) < \infty$, (ii) $M'(W) \geq 0$, (iii) $WM''(W)/M'(W) = 0$, and (iv) M is independent of C and N.

Households choose W and N to minimize the transaction cost per unit of time BN plus the opportunity cost of holding cash per unit of time $M(W)R$:

$$\min_{N,W} BN + RM(W) \ \text{ subject to } WN = C \tag{1}$$

where, since the objective function is homogeneous of degree one in (B, R), we can treat B/R as a parameter.

This version of the model is a small generalization of Baumol–Tobin since, in that model, it is assumed that households withdraw cash when their balance hits zero and the cash balance decreases by a constant amount per period so that $M(W) = W/2$. We can allow $M(W) = W/2 + \underline{M}$ where $\underline{M}$ is some minimum amount of cash held by households, so long as $\underline{M}$ is independent of C and N. This specification allows households to hoard cash.

Replacing $N = C/W$ we can also write:

$$\min_{W} \frac{C}{W}\frac{B}{R} + M(W)$$

5 We take the determination of C as given. Clearly, some of the factors that determine C are common to the ones that determine other aspects of cash management. This is the main reason for our review of cash management models.

whose first-order condition gives:

$$-\frac{C}{(W^*)^2}\frac{B}{R} + M'(W^*) = 0 \quad \text{or} \quad \frac{(W^*)^2}{C} = \frac{B/R}{M'(W^*)} \tag{2}$$

where we denote the optimal policy as W^* and we note that $(W^*)^2/C = W^*/N^*$.[6]

Implications of the model. To simplify our discussion of the implications of the model we introduce the following notation: $n = \log N^*$, $w = \log W^*$, $c = \log C$, and $b = \log B/R$ and

$$w_b \equiv \frac{\partial \log W^*}{\partial \log B/R}, \quad w_c \equiv \frac{\partial \log W^*}{\partial \log C}, \quad n_b \equiv \frac{\partial \log N^*}{\partial \log B/R}, \quad n_c \equiv \frac{\partial \log N^*}{\partial \log C}$$

Problem (1) gives the following four implications:

1. The optimal $\frac{W^*}{N^*}$ is independent of C, and is strictly increasing in B/R.
2. The elasticity of W^* with respect to C is 1/2, i.e.: $w_c = 1/2$.
3. The elasticity of W^* with respect to B/R is positive, i.e.: $0 < w_b$.
4. The sum of the elasticities of W^* and N^* with respect to B/R is zero, and the sum of the elasticities of W^* and N^* with respect to C are one, i.e. $w_b + n_b = 0$ and $w_c + n_c = 1$.

Thus, the elasticity of the ratio W^*/N^* with respect to B/R equals twice the elasticity of W^* with respect to B/R, i.e.

$$\frac{\partial \log(W^*/N^*)}{\partial \log(B/R)} = 2\,w_b > 0 \text{ which is independent of } C. \tag{3}$$

We will use this property in our estimation.[7]

Cash Management and COVID-19. We will next use the above implications to estimate how the COVID-19 pandemic has affected cash management. We hypothesize that the intensity of COVID-19 affects both total cash expenditures C and the cost of cash withdrawals B. The pandemic affects C changing total expenditures and the fraction of total expenditures paid in cash. We might naturally assume that both channels imply that increasing infections in a community

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6 There exists a unique solution for W^* since $(W^*)^2/C$ is increasing in W^*, with elasticity 2, and $\frac{B/R}{M'(W^*)}$ has elasticity smaller than 2 with respect to W^*.

7 Implication 1 follows directly from the first-order condition (2). Implication 2 follows because W^2/C is independent of C and hence the elasticity of W^* must be $\frac{1}{2}$. Implication 4 follows immediately from differentiating the constraint $W^* \times N^* = C$ with respect to B/R and with respect to C. Baumol–Tobin corresponds to $M(W) = W/2$ and thus $M'\frac{1}{2}$. In this case, the elasticity of W^* with respect to B/R is 1/2 and W^*/N^* is not just increasing in B/R, but exactly twice B/R, i.e. the elasticity of W^*/N^* to B/R is one, i.e. $w_b - n_b = 1$. Importantly, the change in households' cost of cash management equals one-half the change in B/R.

will decrease C. Additionally, we hypothesize that increased infection rates will increase the cost of adjusting a cash stock B since adjustments such as ATM withdrawals increase a household's exposure to the virus. We concentrate on measuring this second effect, using the property implied by the theory to separate out the effect of cash expenditures on C. In particular, in the case of the model of this section, the ratio W^*/N^* does *not* depend on C. Under these assumptions, the direct effect of the pandemic on W^*/N^*, divided by twice the elasticity of W^* with respect to B/R, gives the increase in B/R due to the risk of COVID-19.

2.2 Beyond Baumol–Tobin

In this section, we derive similar implications for any model in which the constraint $WN = C$ holds and W and N are functions of B/R and C (e.g. Miller and Orr 1966; Alvarez and Lippi 2009). Differentiating the log of $W^*(C, B/R) \times N^*(C, B/R) = C$:

$$w_b + n_b = 0 \quad \text{and} \quad w_c + n_c = 1 \tag{4}$$

Let $\hat{w}$ and $\hat{n}$ be the total difference in w and n with respect to changes on b and c. Then, we can write:

$$\hat{w} = w_b\hat{b} + w_c\hat{c} \quad \text{and} \quad \hat{n} = n_b\hat{b} + n_c\hat{c}$$

and using Eq. (4) we get:

$$\hat{w} - \hat{n} = 2w_b\hat{b} + \left[2w_c - 1\right]\hat{c} \tag{5}$$

Note that in Section 2 we use $w_b > 0$ (Implication 3) and $w_c = 1/2$ (Implication 2) to recover that the logarithm of the changes of the ratio W^*/N^*, i.e. $\hat{w} - \hat{n}$, depends only on $\hat{b}$. This is $\hat{w} - \hat{n}$ does *not* depend on $\hat{c}$. However, if the elasticity $w_c \neq 1/2$, then changes on $\hat{c}$ will have an impact on $\hat{w} - \hat{n}$, and $\hat{w} - \hat{n} \neq \hat{b}$. This theoretical property suggests that we should include $\hat{c}$ in our empirical specifications in order to avoid a potential omitted-variable bias.

We finish this section by noting that the models described so far apply to a steady state: they describe households' decisions taken to minimize cost with constant parameters. We use the model to describe data from short periods of time (every two weeks) for comparative statics while ignoring the dynamics, i.e. ignoring the effects of past decisions and of expectations of the future values of relevant variables such as B and R. Two reasons justify our choice to focus on statics, which are not different from the reason why the Diamond–Mortensen–Pissarides model is often used in similar fashion. First, we focus on measuring W and N in the data. The state of the households' problem is the stock of cash or cash balances. After any adjustment, this state value is reset, so that there is no memory. Given that adjustments (e.g. visits to a bank branch or ATM) occur approximately twice per month in the data, two-week periods are a good approximation. Second, for essentially the same reasons, expectations about values of B and R far away in the future are not relevant to current decisions, i.e. the optimal decisions in this case are almost identical to those taken in the steady state under the current parameter values.

3 Data

We use data about ATM transactions and withdrawals from Argentina, Chile and the US. We see these data sets as complementary. The countries differ greatly in the usage of cash. Cash is the main payment method used in Argentina and Chile, both in terms of the number of transactions and the value of payments, whereas cash accounts for only a small share of the total value of payments in the US. The data for Argentina comes from a large bank, covers all provinces in the country, and is collected directly from *ATM transactions*. The data set is at the daily level. The data set for Chile covers all banks and provinces and is also collected from ATM transactions, but is only available at the monthly level. The virus was most relevant in Chile around the months of June and July and in Argentina around October. The data for the US, on the other hand, is collected from *card transactions* and covers most counties in the US. The data set is available at the daily level. Since the number of US counties far exceeds the number of Argentinean and Chilean provinces, and the virus spread much earlier in the US, the data offer more variation for our analysis. Importantly, the US data include total expenditures and card expenditures, which allow us to estimate the changes in the transaction cost of using cash through the lens of models that generalize Baumol–Tobin. Remarkably, results for Argentina, Chile, and the US are similar in qualitative and quantitative terms.[8]

3.1 ATM Data: Argentina

We use proprietary data of ATM transactions from Banco Bilbao Vizcaya Argentaria (BBVA) Argentina. BBVA is the third-largest private financial institution in Argentina. The data include all transactions at BBVA's ATMs, including those from clients and non-clients. The data set includes information on the number of transactions and size of withdrawals at the branch level. The data set

8 Although we do not have information on the size of withdrawals, in Section D we include evidence from ATM transactions in Mexico, which is also consistent with the evidence from Argentina, Chile, and the US.

includes information from 135 localities and 24 provinces. We also obtain information on the daily COVID-19 cases and deaths from COVIDSTATS. The source of the information is the Ministry of Health of Argentina. The data begin the day the first case was confirmed in the country, March 3rd, 2020.

Table B1 shows daily averages of our main variables at the locality level. The average locality in our data has 823.33 (std. 2769.90) ATM transactions per day. The size of the disbursement per transaction is 103.44 USD (std. 17.87). The table also reports the average changes in confirmed cases and deaths in each 14-day period. Over our sample period, the average locality saw an increase of approximately 641.08 new confirmed cases every two weeks.

3.2 ATM Data: Chile

We obtain data of ATM transactions from the Financial Market Commission (CMF), a public institution whose main objective is to safeguard the proper functioning, development and stability of the financial market. The data set is at the monthly level. We use data until November 2020. The data set includes, for every bank and commune in Chile, information on the number of ATMs, the number of transactions, and the size of withdrawals. The data set includes information from 17 banks and 346 communes. We also obtain information on the daily COVID-19 cases and deaths from the Ministry of Health of Chile. The data begin the day the first case was confirmed in the country, March 3rd, 2020.

Table C1 shows daily averages of our main variables at the commune level. The average commune in our data has 22,940.95 (std. 83,756) ATM transactions per month. The size of the disbursement per transaction is 90.69 USD (std. 16.60). The table also reports the average changes in confirmed cases and deaths in each month. Over our sample period, the average commune saw an increase of approximately 2182.5 new confirmed cases per month.

3.3 Card Data: United States

Our data on ATM withdrawals come from Facteus, a provider of financial data for business analytics. The data set contains information on the total expenditures, total number of transactions, and total number of cards, at the zip-code level and with daily frequency. Approximately 10 million debit cards are included. The data set begins in 2017 and ends in the first week of July 2020. It contains information of about 32,285 zip codes out of which 28,104 saw at least one ATM transaction in 2020.[9] The debit cards in the Facteus panel are issued by “challenger banks”,

9 Figure A1 shows that the data cover approximately 3199 counties in the US.

which are newer banks that tend to serve underbanked consumers, payroll cards issued by employers for direct debit of wages to employees, government cards issued to access funds from garnished wages, and general-purpose debit cards that can be loaded with cash deposits or via direct deposit and can be used at ATMs to withdraw cash. The cardholders whose transactions are in the data tend to come from the middle- and lower-income brackets, a segment of the population that is both more likely affected by COVID-19 financially and more likely to make cash payments.[10]

The data set includes information of more than 200 Merchant Category Codes (MCCs), which correspond to the MCC standard as maintained by Visa and Mastercard. Every transaction processed by the card networks is assigned an MCC, which is a four-digit number that denotes the type of business providing a service or selling merchandise. MCCs determine whether a business transaction needs to be reported to the IRS and the percentage of each transaction a business needs to pay to the credit-card processor. To select records of households' cash disbursements, we use MCC 6011 ("ATM Cash – Disbursements"), which include cash disbursements at automated teller machines (ATMs) owned, leased, controlled, or sponsored by banks, savings and loans, thrifts, and credit unions, including on-us, and face-to-face transactions.[11]

We also use a database of daily cumulative counts of coronavirus cases and deaths collected by the New York Times. The data set begins with the first reported coronavirus case in Washington State on January 21, 2020, and has been compiled from state and local governments and health departments. Since the data is aggregated at the county level, we aggregate the zip codes of the Facteus panel to

10 The data set offers better coverage of small and mid-sized counties. Figure A2 in the Appendix shows that, as the size of the county increases both in terms of total income and population, the coverage of the data, measured as the share of total expenditures covered in the data relative to the income of the county reported to the IRS, decreases.

11 The data also include MCC 6010 ("Manual Cash Disbursements"), which points to face-to-face cash disbursements at financial institutions. We focus on ATM cash disbursement for two reasons. First, given the sources of the cards included in the data, the coverage of face-to-face cash disbursements is very limited. For example, in the data, debit cards come primarily from challenger banks, which are typically mobile-only banks with no physical branches. As a result, despite the fact that these cards are typically the primary card for the cardholders who own them, over-the-counter cash transactions with these cards are not common. Also, face-to-face transactions are likely to be more affected by temporary closures of bank branches instead of changes in cash-management decisions. Nonetheless, Table A6 shows our main results are robust to including these transactions.

the county level using the U.S. Department of Housing and Urban Development (HUD) United States Postal Service ZIP Code Crosswalk Files.[12]

Table A1 shows summary statistics of our main variables at the county level. The average county in our data has 8.64 (std. 10.75) total ATM transactions per day. The distribution of transactions is right-skewed; the median county has substantially fewer transactions (4.73) than the average county. The average disbursement per transaction in the average county is 149.97 USD (std. 26.3), which is close to the average value of ATM cash withdrawals of 156 USD reported in the 2019 Federal Reserve Payments Study. The share of cash expenditures, measured as the ratio of total ATM disbursements to total expenditures, is 0.13. The share of transactions at ATMs relative to total transactions is 0.03; transactions that do not include ATM disbursements are small in size. Indeed, the average transaction in the average county is approximately 37.78 USD. The table also reports the average changes in the confirmed cases and deaths in a 14-day period. Over our sample period, the average county recorded approximately 64 new confirmed cases every two weeks.

Panel (a) of Figure 2 shows the relationship between the share of cash expenditures and the income per capita of each county. The panel shows a negative relationship; counties with higher income per capita have a lower share of cash expenditures in our data. This is consistent with Kumar, Maktabi, and O'Brien (2018) who show using the 2018 Diary of Consumer Payment Choice (DCPC) that for individuals in households below the median of the income distribution, cash is the most common form of payment and that, as income rises, other payment methods replace cash as the most commonly used payment instrument.[13]

4 Empirical Strategy

4.1 COVID Index

We begin by defining a measure that summarizes the intensity of the COVID-19 pandemic. The total number of confirmed cases or the total number of deaths would be natural choices, but both present measurement challenges. At the local level, the total counts of cases and deaths are often updated when

12 Since zip codes typically overlap with many countries, we use the ratio of residential addresses in the zip-county to the total number of residential addresses in the entire zip code to proportionally distribute the total transactions and disbursements of a zip code to the proper county.

13 Cash is still the most frequently used payment instrument, representing 30 percent of all transactions. It is used, however, predominantly for small-value purchases; its share of value is approximately 8–9%.

local governments correct errors or when they relocate cases to other regions.[14] Furthermore, accurate measurements of the total number of cases depend on the amount and accuracy of the testing taking place in the country or region. Moreover, the total number of deaths registered may be subject to large percentage fluctuations because the underlying number of deaths in a region may be small. To alleviate these concerns we define: $\text{COVID index}_{it} \equiv (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} stands for the total confirmed cases in region i over the last 14 days and Deaths_{it} stands for the total confirmed deaths. We choose the 14-day difference to increase the accuracy of the measurements and because it is the length of the observation period for people who have been exposed to the virus.

We also construct a leave-out COVID index, which we use as an instrument to further alleviate concerns around classical measurement errors. The leave-out COVID index is constructed using $\overline{\text{Cases}}_{it} = \sum_{j\neq i}\omega_{ij}\text{Cases}_{jt}$ and $\overline{\text{Deaths}}_{it} = \sum_{j\neq i}\omega_{ij}\text{Deaths}_{jt}$, where ω_j represents the share of workers commuting to county i from county j normalized so that $\sum_{j\neq i}\omega_{ij} = 1$.[15]

4.2 Motivating Facts: Argentina and Chile

Panel (a) of Figure 1 shows the evolution of both total transactions and the average size of withdrawal for Argentina. The dashed vertical line marks the day of the first positive case of COVID-19 in Argentina. The panel shows that during the pandemic the average size of a withdrawal has increased considerably and the number of ATM transactions has decreased. Panel (c) shows that similar patterns can be seen from the Chilean data.

Viewed through the lens of the Baumol–Tobin model, the pandemic has increased households' transaction cost of adjusting their stock of cash (e.g. "making trips to the bank" to obtain cash). In the theory, this can be denoted as B/R. Since W/N, the ratio of the size of each withdrawal to the number of withdrawals per unit of time, is strictly increasing in B/R and is observable in our data, we study the relationship between this ratio and COVID index. Panels (b) and (c) show that, in the time-series, the households' transaction cost of adjusting their stock of cash has increased and that the timing of this change coincides with the increasing spread of COVID-19 in both countries.

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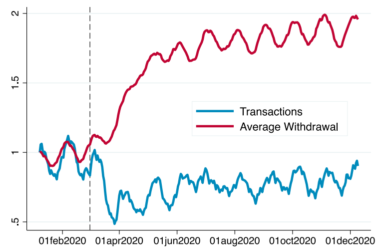
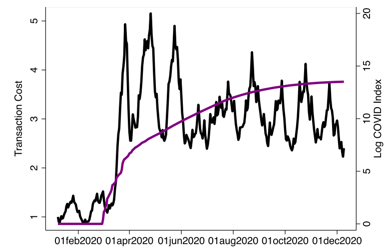
14 For Argentina we mainly use localities, except for the Autonomous City of Buenos Aires where we can obtain ATM transactions and COVID-19 information at the neighborhood ("barrio") level. For Chile we use communes and for the US we focus on counties.

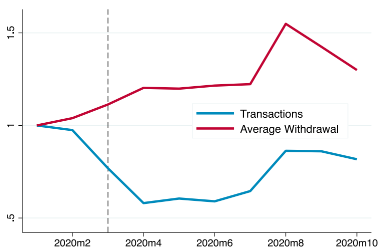
15 We obtain the commuting flows for each county from the 2011–2015 American Community Survey (ACS). The ACS asks respondents about their primary workplace location. When information about workers' residence location and workplace location are coupled, a commuting flow is generated.



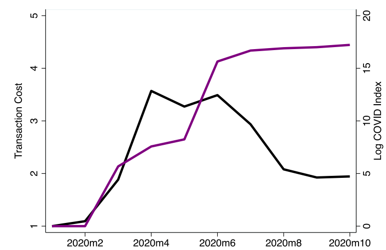
(a) Argentina: Transactions & Withdrawals



(b) Argentina: Costs & COVID-19 Cases



(c) Chile: Transactions & Withdrawals



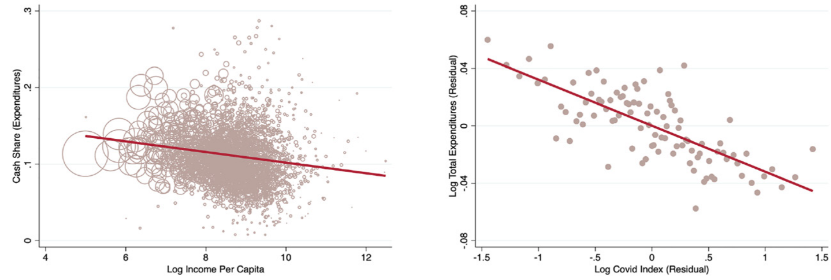
(d) Chile: Costs & COVID-19 Cases

Figure 1: COVID-19 and the use of cash: Argentina and Chile.
Panel (a) shows the evolution of both total transactions and the average withdrawal size in Argentina. Both are two-week moving averages normalized to 1 on the first day of 2020. The dashed vertical line marks the day of the first positive case of COVID-19 in Argentina. Panel (b) shows the relationship between the transaction cost of adjusting the stock of cash (W/N) in black and the logarithm of COVID index (i.e. COVID index $=$ (Cases)$^{1/2}$(Deaths)$^{1/2}$) in purple. The transaction cost is approximated using the ratio of the average size of withdrawals and the total ATM transactions. Both are two-week moving averages normalized to 1 on the first day of 2020. Panel (c) and (d) show the same relationships for Chile using a monthly data.

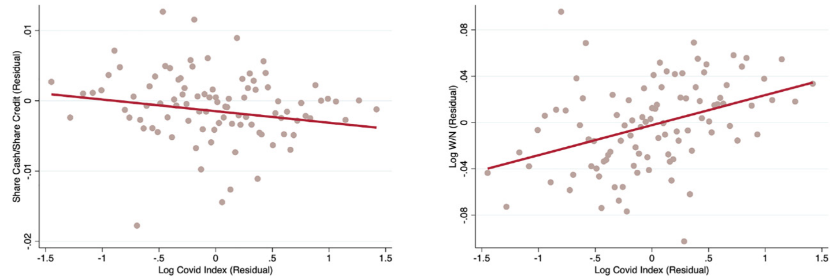
4.3 Motivating Facts: United States

In the US, the pandemic has decreased total spending significantly, which in turn has decreased the need for cash. Panel (b) of Figure 2 illustrates this pattern with the relationship between our COVID index and the total expenditures in each county and two-week period. After controlling for county- and period-fixed effects, we can see that the intensity of the pandemic and total expenditures have a strong negative relationship.

The pandemic has also shifted transactions from cash to alternative methods of payment. This is depicted in Panel (c) of Figure 2 which shows the relation between the cash-credit share and COVID index, where the share of



(a) Share of Cash Expenditures and Income (b) Total Expenditures



(c) Cash-Credit (d) Transaction Cost

Figure 2: COVID-19 and the use of cash: US.
Panel (a) shows the cross-sectional relationship between the average share of cash expenditures and the income per capita at the county level. The share of cash expenditures is computed by averaging across 2017–2019, the years before the virus outbreak. Income is measured using individual income tax returns (Forms 1040) filed with the Internal Revenue Service (IRS) during the 12-month period, January 1, 2017 to December 31, 2017. The population totals come from the US Census. Panel (b) shows the relationship between total spending and the COVID index. Panel (c) shows the relationship between the ratio of the share of spending in cash (ATM disbursements) and the share of spending in card and the COVID index. Panel (d) shows the relationship between the transaction cost of adjusting the stock of cash (W/N) and the COVID index. The transaction cost is approximated using the ratio of the daily average size of withdrawals and the daily average of total ATM transactions for each county at the bi-weekly level. The variables in panels (a)-(d) are plotted after controlling for county and time effects. COVID index$_{it}$ = (Cases$_{it}$)$^{1/2}$(Deaths$_{it}$)$^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the county over the last 14 days and Deaths$_{it}$ are the total confirmed deaths over the last 14 days in county i and period t.

cash expenditures is measured using ATM disbursements and the credit share covers every other payment using a card. The figure shows that, as the pandemic worsens, households prefer to use cards instead of cash, which can be the result of households making more online purchases or simply following the CDC recommendation to use touch-free payment methods.[16]

Panel (d) of Figure 2 shows a strong positive relationship between the logarithm of W/N and the COVID index after controlling for county- and time-differentiated effects, suggesting that the adjustment cost of withdrawing more cash has gone up during the pandemic. Note, however, that in our generalization of Baumol–Tobin, W/N is not independent of C, the units paid in cash per unit of time, which can be affected in the pandemic by changes in total expenditures as well as the cash-credit substitution depicted in Panel (c). This information is available in the US data. Thus, the next section will explore this relationship using a reduced-form approach in order to isolate the impact of COVID-19 infections on the cost of cash adjustment B/R.

4.4 Transaction Cost of Obtaining Cash

To study the effect of COVID-19 intensity on the fixed cost of obtaining cash, we use the following specification

$$\ln Y_{it} = \alpha + \beta \ln \text{COVID index}_{it} + \theta \ln C_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{6}$$

where Y_{it} represents dependent variables such as the number of ATM withdrawals, N_{it}, the average size of cash withdrawals, W_{it}, or the transaction cost of adjusting a stock of cash, $\frac{W_{it}}{N_{it}}$. C_{it} are total cash expenditures approximated using all ATM disbursements in county i at time t. All our specifications include region effects, λ_i, and time effects, θ_t. Since the theoretical results that motivate this specification apply to the steady state, we focus on two-week periods.[17] Moreover, given that the error term could be both serially and cross-sectionally correlated, we use Driscoll and Kraay standard errors.[18]

We begin with the changes in cash management decisions in Argentina. Column (1) in Table 1 indicates that if the intensity of the pandemic doubles, the ratio of W/N increases by approximately 2.2%. This column corresponds to the

16 Households have also been hoarding cash for precautionary reasons. Unfortunately, we are unable to verify this pattern directly from our data, since we can only observe ATM transactions and disbursements. Nonetheless, the Federal Reserve System, Central Bank of Argentina, and Central Bank of Chile report that the currency in circulation during the pandemic has surged to an all time high.

17 Households in the US, for example, withdraw cash from ATMs more than once per month on average (Bagnall et al., 2014).

18 Driscoll–Kraay standard errors tend to be conservative. Our results remain if we use robust standard errors or if we cluster them at the county level; these results are presented in Table A7.

Baumol–Tobin case; recall that an implication of this model is that the ratio of W/N does not depend on the total cash expenditures C and is strictly increasing with the transaction cost B/R. Columns (2) and (3) show that, as predicted by the model, an increase in the prevalence of the virus increases the average size of withdrawals and decreases the number of ATM transactions. Columns (4)–(6) show that these results are robust to controlling for the total cash expenditures, C. This case corresponds to the generalization of Baumol–Tobin in which W/N can be recovered only after controlling for C in order to avoid potential omitted-variable issues. These findings are consistent with the predictions of a wider class of cash management models.[19] Column (6) shows a remarkably similar elasticity for Chile between the prevalence of the virus and the ratio of W/N, approximately 2.4%. Just as in the Argentinean case, both the average size of withdrawals and the number of ATM transactions respond as predicted by cash management models. Columns (10)–(12) show that in the Chilean data our findings are also robust to including the total cash expenditures as control.

Table 2 shows how the transaction cost for cash changed in the US during the pandemic. Column (1) indicates that if the intensity of the pandemic doubles, the ratio W/N increases by 3%. This estimate is again remarkably similar to the estimate from Argentina and Chile. In column (2), we control for the total cash expenditures, C. In this case, the coefficient of the COVID index decreases but it is still positive and significant.

As discussed above, a potential concern is that the number of cases and number of deaths in a given county are measured with error, thus leading to bias in the coefficient of the COVID index. Columns (3) and (4) address this issue by instrumenting the COVID index with a second measurement of COVID index correlated with the original but with an independent measurement error.[20] In column (3) we instrument the COVID index with a one-period lag. In column (4) we instrument the COVID index with the county-level leave-out COVID index. Consistent with the presence of classical measurement error, the coefficient increases in both cases, even after conditioning for total expenditures paid in cash.[21]

Column (5) addresses the endogeneity of the total cash expenditures, which we must address for two reasons. First, some changes in the transaction cost of cash might not be captured by COVID index, and these could be correlated with the total cash expenditures. This effect would yield biased and inconsistent estimates

19 Tables B2 and B3 show these findings are robust to using cases or deaths as the dependent variable.

20 The first stage for all the specifications presented in Table 2 are presented in Table A9.

21 Table A5 shows that we obtain similar results when, instead of using COVID index, we use the total confirmed cases or the total deaths as dependent variables.

Table 1: COVID-19 and the use of cash: Argentina and Chile.

	Argentina					
	(1) Log $\frac{W}{N}$	**(2)** Log W	**(3)** Log N	**(4)** Log $\frac{W}{N}$	**(5)** Log W	**(6)** Log N
Log COVID(t)	0.022***	0.008***	−0.014***	0.017***	0.009***	−0.009***
	(0.006)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Log $C(t)$				−0.810***	0.095***	0.905***
				(0.015)	(0.007)	(0.007)
Observations	2532	2532	2532	2532	2532	2532
Within R-squared	0.512	0.889	0.53	0.742	0.894	0.914
Locality	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
	Chile					
	(7) Log $\frac{W}{N}$	**(8)** Log W	**(9)** Log N	**(10)** Log $\frac{W}{N}$	**(11)** Log W	**(12)** Log N
Log COVID(t)	0.024**	0.004**	−0.020***	0.011**	0.005**	−0.005**
	(0.008)	(0.001)	(0.006)	(0.003)	(0.002)	(0.002)
Log $C(t)$					0.077*	0.923***
				(0.075)	(0.037)	(0.037)
Observations	1873	1873	1914	1873	1873	1873
Within R-squared	0.231	0.700	0.487	0.644	0.711	0.921
Commune	Y	Y	Y		Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). Columns (1)–(6) for Argentina and Columns (7)–(12) for Chile. The dependent variable in columns (1), (4), (7) and (10) is the transaction cost of adjusting the stock of cash. The cost is approximated for Argentina using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each locality at the bi-weekly level. The cost is approximated for Chile using the ratio of the monthly average size of withdrawals and the monthly average of the total ATM transactions for each commune and month. The dependent variable in columns (2), (5), (8), and (11) is the average size of withdrawals and in columns (3), (6), (9) and (12) the dependent variable is the total ATM transactions. The independent variable is the logarithm of the COVID index$_{it}$ = $(\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the region over the last 14 days (last month) and Deaths$_{it}$ are the total confirmed deaths over the last 14 days (last month) in locality (commune) i and period t for Argentina (Chile). In columns (4)–(6) we control for the logarithm of total expenditures paid in cash. We use Driscoll and Kraay standard errors with four lags. All the specifications include region and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

of θ and β, the coefficient of the COVID index. We address this potential bias by instrumenting the total expenditures in cash with the total expenditures, E, and its lagged value. Our identifying assumption is that the unobserved changes in

Table 2: COVID-19 and the use of cash: transaction cost (W/N).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	0.030***	0.015***	0.026**	0.033***	0.008**	0.006*	0.021**
	(0.004)	(0.002)	(0.009)	(0.008)	(0.003)	(0.003)	(0.008)
Log $C(t)$		−0.344***	−0.349***	−0.339***	−0.511***	−0.564***	−0.504***
		(0.020)	(0.025)	(0.026)	(0.039)	(0.052)	(0.041)
Observations	21,009	21,009	17,698	20,914	20,863	20,863	20,856
Within R-squared	0.322	0.426	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable is the logarithm of the COVID index$_{it}$ = $(\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the county over the last 14 days and Deaths$_{it}$ are the total confirmed deaths over the last 14 days in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index$_{it}$ with its one-period lagged value. In column (4) we instrument the logarithm of the COVID index$_{it}$ with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of the total expenditures paid in cash with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total expenditures paid in cash with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index$_{it}$ and the logarithm of total expenditures paid in cash using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

transaction cost affect cash-credit substitutions, but not total household expenditures. In this case, the total expenditures would affect W/N only through cash expenditures. Column (5) shows that in this case the coefficient of the COVID index reduces but remains positive and significant.

The second concern is that households hoard more cash, not only in response to the overall presence of the virus (e.g. an increase in $\underline{M}$), but also in response to an increase in the intensity of infection in their respective counties. In this case, time fixed effects are not enough to control for hoarding and total ATM disbursements would include both the cash households spend and the cash that they hoard. Since our measure of total expenditures suffers from the same issue, we address it by instrumenting the total cash expenditures with the county-level leave-out mean of total expenditures (i.e. $\overline{E}_{it} = \sum_{j\neq i}\omega_{ij}E_{jt}$) and its lagged value. The leave-out instrument is correlated with the total expenditures of people living in county

i, thus correlated with the total cash expenditures of those households, and it does not include the hoarding behavior of households in county i responding to the pandemic. Column (6) shows that in this case our results are similar to those shown in column (5).

In the last column, we instrument both the COVID index using our leave-out instrument and cash expenditures using total expenditures and its lagged value. We instrument both variables in order to address the measurement error of the COVID-19 variables and the endogeneity of cash expenditures simultaneously. Column (7) shows that if the intensity of the pandemic doubles, the ratio W/N increases by approximately 2%. Overall, we find very consistent results throughout all the specifications. The current pandemic, viewed through the lens of cash management models, has increased the transaction cost of using cash.[22]

Next, we use the average size of withdrawals as a dependent variable. The results are presented in Table A2, which shows that when we control for total cash expenditures, the COVID index has a positive and significant coefficient on the average withdrawal size. Column (2) shows that doubling the intensity of COVID-19 increases the average size of withdrawals by approximately 1.5%. Column (8) shows that when we instrument the COVID index and total cash expenditures, we obtain a similar estimate, an increase of approximately 2.1%. Unsurprisingly, the COVID-19 pandemic also had a significant negative impact on the number of transactions, N. These results are presented in Table A3 and in Table A4, where we use a Poisson model. Thus, the COVID-19 pandemic has led to an increase in the transaction cost of using cash which, consistent with the prediction of cash management models, has increased the overall size of withdrawals and has decreased the frequency of ATM transactions.[23]

4.5 Cash-Credit Substitution

Lastly, we show that COVID-19 has disrupted households' choices of payment methods in the US. We use as a dependent variable the logarithm of the ratio of expenditures paid in cash and those paid in card, including debit and credit payments. The coefficient of the independent variables in this case combines: (i)

22 Table A6 shows that our results are similar when we include face-to-face cash disbursements in our measures of cash transactions and withdrawals.

23 In the Appendix we show that the response of ATM transactions to the pandemic is quantitatively similar in Mexico (Table D2). We also use data at the bank-municipality level to show that, consistent with cash management models, branch closures due to COVID-19 have a substantial impact on ATM transactions even after controlling for municipality-time, bank-time, and bank-municipality effects (Table D3).

Table 3: COVID-19 and the use of cash: cash-credit response.

	(1)	(2)	(3)	(4)	(5)
Log COVID(t)	-0.011^{***}			-0.025^{*}	-0.023^{**}
	(0.003)			(0.013)	(0.008)
Log Cases(t)		-0.007^{***}			
		(0.002)			
Log Deaths(t)			-0.008^{***}		
			(0.002)		
Observations	21,008	21,008	21,008	17,698	20,914
Within R-squared	0.202	0.202	0.202	–	–
County	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the logarithm of the ratio of expenditures paid in cash and those paid in card. The independent variable in columns (1), (4) and (5) is the logarithm of the COVID index$_{it}$ = $(\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the county over the last 14 days and Deaths$_{it}$ are the total confirmed deaths over the last 14 days in county i and period t. In column (2) the independent variable is the logarithm of Cases$_{it}$ and in column (3) is the logarithm of Deaths$_{it}$. In column (4) we instrument the logarithm of the COVID index$_{it}$ with its one-period lagged value. In column (5) we instrument the logarithm of the COVID index$_{it}$ with a leave-out instrument as described in the main text. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

the impact of changes in the cost of obtaining cash, (ii) the impact of changes in the cost of using cash relative to cards, and (iii) the elasticity of substitution between cash and cards. Column (1) in Table 3 shows that an increase in the prevalence of the virus has led to a decrease in cash payments relative to card payments, which is consistent with increases in the cost of both obtaining and using cash. Columns (2) and (3) show that this result holds if we consider total cases and total deaths separately. Columns (4) and (5) instrument the COVID index with its lagged value and with the leave-out COVID index, respectively, in order to ameliorate measurement error concerns. These columns indicate that if the prevalence of the virus doubles in a county, total cash expenditures relative to card expenditures decrease approximately 2.3–2.5%.

If households hoard more cash in response to an increase in the intensity of the pandemic in their respective counties, these estimates are a lower bound of the change in the cash/card choice of households. This is because we can only approximate total cash expenditures using total cash withdrawals. Nonetheless, we find the magnitude of these coefficients to be remarkably low; a very large increase in the COVID index (100 log points) implies a very small change in the cash/card choice of households. This result is consistent with previous work estimating the elasticity of substitution between cash and cards. Both Alvarez and Argente (2020a) and Alvarez and Argente (2020b) found low values of this parameter for Uber rides in Mexico. These papers, using large-scale experiments and an actual ban on cash payments respectively, estimate that a 10% change in the price of the same good paid in cash (Uber rides) implies a change in the ratio of purchases paid in cash relative to those paid in cards of 30–50%. Unfortunately, there are very few estimates of the elasticity of substitution between cash and cards in the literature. Obtaining accurate estimates of this parameter is of crucial importance to estimate the welfare effects of policies restricting the use of cash.

5 Conclusion

During the COVID-19 pandemic, households have decreased their purchases paid in cash both because spending has decreased and because they are using alternative payment methods instead. Additionally, households have changed their cash management behavior. In particular, households have reduce the average size and frequency of cash withdrawals. We use the classical Baumol–Tobin model and simple generalization to disentangle these effects. We show that households' observed cash management behavior is consistent with an increase in the transaction cost of using cash in locations-periods with higher prevalence of COVID-19. Moreover, the estimates are robust to several forms of measurement error and endogeneity, and remarkably similar across the US, Chile, and Argentina. Finally, for the US – where we have more complete data – we found that the ratio of payments using cash relatively to those using cards decreases with the prevalence of COVID-19. However, the magnitude of this effect is small, consistent with a low elasticity of substitution between cash and cards.

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Appendix A: United States

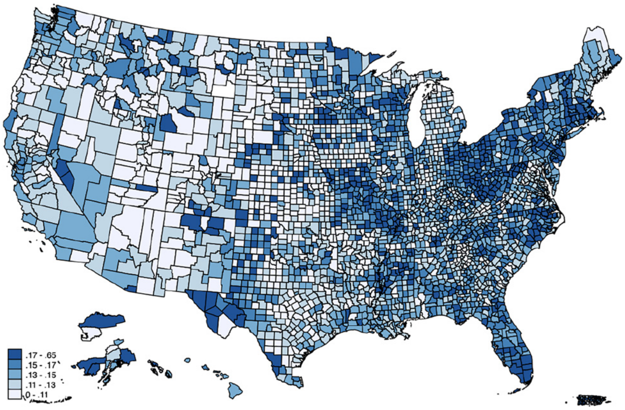

Figure A1: Share of cash expenditures by County.
The figure shows the share of cash expenditures (ATM disbursements) over the total expenditures, at the county level. The data include information of 3199 counties.

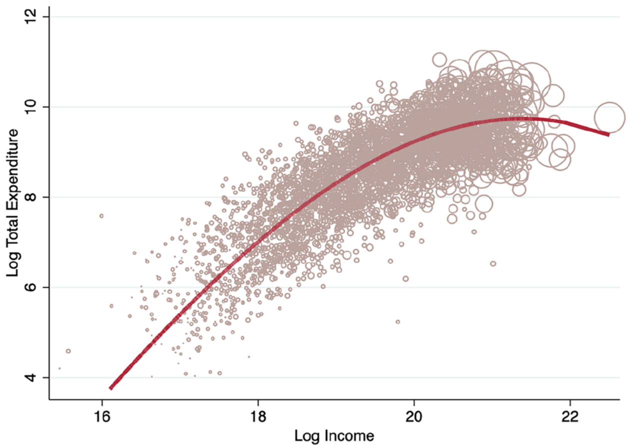

Figure A2: Total expenditures and Income.
The figure shows the relationship between total spending and total income in a county. Total spending is computed averaging across 2017–2019. Income is measured using individual income tax returns (Forms 1040) filed with the Internal Revenue Service (IRS) between January 1, 2017 and December 31, 2017. The size of the marker indicates the size of the population in each county obtained from the US Census.

Table A1: Summary statistics – County level (US).

	(1) Mean	(2) Std. Dev.	(3) Pct. 25	(4) Median	(5) Pct. 75
ATM transactions	8.64	10.75	1.51	4.73	11.94
ATM disbursements	1252.66	1485.06	232.92	713.08	1747.41
ATM disbursements per transaction	149.97	26.30	136.50	147.08	159.53
Share of cash expenditures (expenditures)	0.13	0.04	0.11	0.13	0.15
Share of cash expenditures (transactions)	0.03	0.01	0.03	0.03	0.04
Total expenditures	9311.48	10,460.00	1859.56	5732.00	13,260.34
Total transactions	249.28	278.01	50.46	155.48	352.65
Total expenditures per transaction	37.78	6.40	34.58	36.84	39.41
New COVID-19 cases (bi-weekly)	64.25	300.27	1.71	6.69	27.72
New COVID-19 deaths (bi-weekly)	2.57	13.92	0.00	0.08	0.69

The table shows descriptive statistics of the variables of interest at the county level (mean, standard deviation, 25th percentile, median, and 75th percentile) in the year 2020. The share of cash expenditures (Expenditures) is the total cash expenditures over the total expenditures, including ATM disbursements and card transactions. The share of cash expenditures (Transactions) indicates the total ATM transactions over the total transactions. The variables presented are daily averages, except those that relate to the COVID-19 pandemic. "New COVID-19 Cases" indicates the changes in the confirmed cases in a 14-day period at the county level. "New COVID-19 Deaths" indicates the changes in the confirmed deaths in a 14-day period at the county level. The average of these variables is taken after the first case was confirmed on January 21st, 2020.

Table A2: COVID-19 and the use of cash: withdrawals (*W*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	−0.006***	0.008***	0.013**	0.017***	0.004**	0.003*	0.010**
	(0.002)	(0.001)	(0.005)	(0.004)	(0.001)	(0.002)	(0.004)
Log $C(t)$		0.328***	0.326***	0.331***	0.244***	0.218***	0.248***
		(0.010)	(0.012)	(0.013)	(0.019)	(0.026)	(0.021)
Observations	21,009	21,009	17,698	20,914	20,863	20,863	20,856
Within R-squared	0.094	0.454	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the daily average size of withdrawals. The independent variable is the logarithm of the COVID $\text{index}_{it} = (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} are the total confirmed cases in the county over the last 14 days and Deaths_{it} are the total confirmed deaths over the last 14 days in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index_{it} with its one-period lagged value. In column (4) we instrument the logarithm of the COVID index_{it} with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of total cash expenditures with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total cash expenditures with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index_{it} and the logarithm of total cash expenditures using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table A3: COVID-19 and the use of cash: transactions (N).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	-0.036^{***}	-0.008^{***}	-0.013^{**}	-0.017^{***}	-0.004^{**}	-0.003^{*}	-0.010^{**}
	(0.005)	(0.001)	(0.005)	(0.004)	(0.001)	(0.002)	(0.004)
Log $C(t)$		0.672^{***}	0.674^{***}	0.669^{***}	0.756^{***}	0.782^{***}	0.752^{***}
		(0.010)	(0.012)	(0.013)	(0.019)	(0.026)	(0.021)
Observations	21,009	21,009	17,698	20,914	20,863	20,863	20,856
Within R-squared	0.365	0.831	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable is the logarithm of the COVID $\text{index}_{it} = (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} are the total confirmed cases in the county over the last 14 days and Deaths_{it} are the total confirmed deaths over the last 14 days in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index_{it} with its one-period lagged value. In column (4) we instrument the logarithm of the COVID index_{it} with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of total expenditures paid in cash with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total expenditures paid in cash with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index_{it} and the logarithm of total expenditures paid in cash using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table A4: COVID-19 and the use of cash: transactions (N) – Poisson.

	(1)	(2)	(3)	(4)	(5)	(6)
Log COVID(t)	-0.033^{***}	-0.007^{***}				
	(0.003)	(0.001)				
Log Cases(t)			-0.025^{***}	-0.004^{***}		
			(0.002)	(0.001)		
Log Deaths(t)					-0.017^{***}	-0.006^{***}
					(0.003)	(0.001)
Log $C(t)$		0.694^{***}		0.695^{***}		0.696^{***}
		(0.005)		(0.005)		(0.006)
Observations	20,921	20,921	20,921	20,921	20,921	20,921
County	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6) using a Poisson model. The dependent variable is the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable in columns (1) and (2) is the logarithm of the COVID index$_{it}$ = (Cases$_{it}$)$^{1/2}$(Deaths$_{it}$)$^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the county over the last 14 days and Deaths$_{it}$ are the total confirmed deaths over the last 14 days in county i and period t. The independent variable in columns (3) and (4) is the total confirmed cases in the county over the last 14 days and in columns (5) and (6) is the total confirmed deaths over the last 14 days in county i and period t. In columns (2), (4), and (6) we control for the logarithm of total expenditures paid in cash. We consider county-biweek pairs with at least 5 ATM transactions and use bootstrap standard errors. All the specifications include county and time effects. The ***, represent statistical significance at 1% level.

Table A5: Cases, deaths, and the use of cash: transaction cost (W/N).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Cases(t)	0.018***	0.008***	0.013**	0.015*				
	(0.003)	(0.002)	(0.005)	(0.007)				
Log Deaths(t)					0.021***	0.014***	0.032***	0.044***
					(0.003)	(0.003)	(0.009)	(0.009)
Log $C(t)$		−0.345***	−0.350***	−0.341***		−0.346***	−0.352***	−0.343***
		(0.020)	(0.025)	(0.027)		(0.021)	(0.025)	(0.026)
Observations	21,009	21,009	17,698	20,914	21,009	21,009	17,698	20,916
Within R-squared	0.321	0.425	–	–	0.32	0.426	–	–
County	Y	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable in columns (1) to (4) is the total confirmed cases in the county over the last 14 days and in columns (5) to (8) is the total confirmed deaths over the last 14 days in county i and period t. In columns (2) and (6) we control for the logarithm of total expenditures paid in cash. In columns (3) and (7) we instrument the logarithm of the total confirmed cases and the total deaths with their respective lag variables. In columns (4) and (8) we instrument the logarithm of the total confirmed cases and the total deaths with a leave-out instrument as described in the main text. We consider county-biweek pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table A6: COVID-19 and the use of cash: transaction cost (W/N) – all cash transactions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	0.027***	0.016***	0.022*	0.031***	0.008**	0.005	0.017*
	(0.004)	(0.003)	(0.010)	(0.009)	(0.003)	(0.004)	(0.009)
Log $C(t)$		−0.263***	−0.266***	−0.258***	−0.460***	−0.539***	−0.454***
		(0.032)	(0.040)	(0.039)	(0.058)	(0.075)	(0.060)
Observations	21,165	21,165	17,820	21,067	21,016	21,016	21,009
Within R-squared	0.385	0.434	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The estimates include MCC 6010 ("Manual Cash Disbursements"), which includes face-to-face cash disbursements at financial institutions. The dependent variable is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average of withdrawals and the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable is the logarithm of the COVID $\text{index}_{it} = (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} are the total confirmed cases in the county over the last 14 days and Deaths_{it} are the total confirmed deaths over the last 14 days in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index_{it} with its one-period-lagged value. In column (4) we instrument the logarithm of the COVID index_{it} with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of total expenditures paid in cash with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total expenditures paid in cash with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index_{it} and the logarithm of total expenditures paid in cash using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table A7: COVID-19 and the use of cash: transaction cost (W/N) – alternative standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	0.030***	0.015***	0.026***	0.033***	0.008***	0.006**	0.021***
	(0.003)	(0.002)	(0.006)	(0.005)	(0.003)	(0.003)	(0.005)
Log C(t)		−0.344***	−0.349***	−0.339***	−0.511***	−0.564***	−0.504***
		(0.010)	(0.010)	(0.010)	(0.014)	(0.019)	(0.014)
Observations	20,921	20,921	17,698	20,914	20,863	20,863	20,856
Within R-squared	0.007	0.159	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each county at the bi-weekly level. The independent variable is the logarithm of the COVID $\text{index}_{it} = (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} are the total confirmed cases in the county over the last 14 days and Deaths_{it} are the total confirmed deaths over the last 14 days in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index_{it} with its one-period lagged value. In column (4) we instrument the logarithm of the COVID index_{it} with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of total expenditures paid in cash with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total expenditures paid in cash with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index_{it} and the logarithm of total expenditures paid in cash using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and cluster the standard errors at the county level. All the specifications include county and time effects. The *** and **, represent statistical significance at 1% and 5% levels, respectively.

Table A8: COVID-19 and the use of cash: transaction cost (W/N) – monthly.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log COVID(t)	0.025***	0.013***	0.088***	0.013**	0.009***	0.008***	0.008
	(0.003)	(0.003)	(0.018)	(0.005)	(0.003)	(0.003)	(0.005)
Log $C(t)$		−0.435***	−0.419***	−0.435***	−0.584***	−0.636***	−0.584***
		(0.013)	(0.015)	(0.013)	(0.019)	(0.024)	(0.020)
Observations	11,860	11,860	8976	11,860	11,853	11,853	11,853
Within R-squared	0.008	0.228	–	–	–	–	–
County	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each county at the monthly level. The independent variable is the logarithm of the COVID $\text{index}_{it} = (\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases_{it} are the total confirmed cases in the county over the last month and Deaths_{it} are the total confirmed deaths over the last month in county i and period t. In column (2) we control for the logarithm of total expenditures paid in cash. In column (3) we instrument the logarithm of the COVID index_{it} with its one-period lagged value. In column (4) we instrument the logarithm of the COVID index_{it} with a leave-out instrument as described in the main text. In column (5) we instrument the logarithm of total expenditures paid in cash with the logarithm of total expenditures and its lagged value. In column (6) we instrument the logarithm of total expenditures paid in cash with a leave-out instrument of the logarithm of total expenditures and its lagged value. In column (7) we instrument both the COVID index_{it} and the logarithm of total expenditures paid in cash using the leave out instrument and the logarithm of total expenditures and its lagged value. We consider county-monthly pairs with at least 5 ATM transactions and cluster the standard errors at the county level. All the specifications include county and time effects. The *** and **, represent statistical significance at 1% and 5% levels, respectively.

Table A9: COVID-19 and the use of cash: transaction cost (W/N) – first stage.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log COVID(t)		Log $C(t)$		Log COVID(t)	Log $C(t)$
Log COVID($t-1$)	0.474***					
	(0.039)					
Log COVID($t-1$) – IV		0.734***			0.718***	−0.006
		(0.006)			(0.009)	(0.005)
Log $C(t)$	−0.214***	−0.117**				
	(0.036)	(0.040)				
Log $E(t)$			1.117***		−0.230***	1.087***
			(0.014)		(0.022)	(0.031)
Log $E(t-1)$			−0.104***		−0.236**	−0.072
			(0.024)		(0.090)	(0.043)
Log $E(t)$ – IV				0.968***		
				(0.035)		
Log $E(t-1)$ – IV				0.013		
				(0.026)		
Log COVID(t)			−0.009***	−0.019***		
			(0.002)	(0.004)		
Observations	17,819	21,002	20,951	20,951	20,944	28,068

Table A9: (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log COVID(t)		Log $C(t)$		Log COVID(t)	Log $C(t)$
F-statistic	105.5	7422.7	2257.8	333.6	1577.6	1413.4
County	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The tables shows the first-stage regressions of the instrumented specifications in Table 2. In columns (1) and (2) the instrumented variable is the logarithm of the COVID index$_{it}$ = $(\text{Cases}_{it})^{1/2}(\text{Deaths}_{it})^{1/2}$, where Cases$_{it}$ are the total confirmed cases in the county over the last 14 days and Deaths$_{it}$ are the total confirmed deaths over the last 14 days in county i and period t. In column (1) the instrument is the lagged value of COVID index. In column (2) the instrument is a leave-out instrument of the mean of COVID index at the county level where we use the commuting flows as weights. In both columns we control for total cash expenditures. In columns (3) and (4) the instrumented variable is total cash expenditures. In column (3) the instruments are the logarithm of total expenditures and its lagged value. In column (4) the instrument is a leave-out instrument of the logarithm of total expenditures and its lagged value. In both columns we control for COVID index. The estimates in columns (5) and (6) correspond to those presented in column (8) of Table 2, where we instrument both Log COVID index and Log C(t). In column (5) we instrument COVID index with a leave-out instrument of the mean of COVID index at the county level. In column (6) we instrument Log C(t) with the logarithm of total expenditures and its lagged value. We consider county-two-week pairs with at least 5 ATM transactions and use Driscoll and Kraay standard errors with four lags. All the specifications include county and time effects. The *** and **, represent statistical significance at 1% and 5% levels, respectively.

Appendix B: Argentina

Table B1: Summary statistics – locality level (Argentina).

	(1) Mean	(2) Std. Dev.	(3) Pct. 25	(4) Median	(5) Pct. 75
ATM transactions	823.33	2769.90	319.70	461.47	685.32
ATM disbursements	80,982.04	258,954.65	34,888.18	51,003.71	70,525.66
ATM disbursements per transaction	103.44	17.87	91.71	102.19	114.49
New COVID-19 cases (bi-weekly)	641.08	1255.20	168.81	331.98	685.23
New COVID-19 deaths (bi-weekly)	20.12	43.11	2.87	8.68	24.14

The table shows descriptive statistics of the variables of interest at the locality level (mean, standard deviation, percentile 25th, median, and percentile 75th) in the year 2020. The exchange rate used is the one that prevailed on January 1, 2020 (i.e. 1 Argentine Peso equals 0.01671 United States Dollar); all amounts are expressed in real dollars. The variables presented are daily averages, except those that relate to the COVID-19 pandemic. "New COVID-19 Cases" indicates the changes in the confirmed cases in a 14-day period at the locality level. "New COVID-19 Deaths" indicates the changes in the confirmed deaths in a 14-day period at the locality level. The average of these variables is taken after the first case was confirmed on March 3rd, 2020.

Table B2: Cases and the use of cash: Argentina.

	(1) $\text{Log}\ \frac{W}{N}$	(2) Log W	(3) Log N	(4) $\text{Log}\ \frac{W}{N}$	(5) Log W	(6) Log N
Log Cases(t)	0.019***	0.006***	−0.012***	0.014***	0.007***	−0.007***
	(0.005)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
Log $C(t)$				−0.808***	0.096***	0.904***
				(0.014)	(0.007)	(0.007)
Observations	2532	2532	2532	2532	2532	2532
Within R-squared	0.514	0.889	0.531	0.742	0.894	0.914
Locality	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6) for Argentina. The dependent variable in columns (1) and (4) is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each locality at the bi-weekly level. The dependent variable in columns (2) and (5) is the average size of withdrawals and in columns (3) and (6) the dependent variable is the total ATM transactions. The independent variable is the logarithm of the total confirmed cases over the last 14 days in locality i and period t. In columns (4)–(6) we control for the logarithm of total expenditures paid in cash. We use Driscoll and Kraay standard errors with four lags. All the specifications include locality and time effects. The ***, represent statistical significance at 1% level.

Table B3: Deaths and the use of cash: Argentina.

	(1) Log $\frac{W}{N}$	(2) Log W	(3) Log N	(4) Log $\frac{W}{N}$	(5) Log W	(6) Log N
Log Deaths(t)	0.016***	0.006***	−0.010**	0.013***	0.007***	−0.007***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Log $C(t)$				−0.814***	0.093***	0.907***
				(0.015)	(0.008)	(0.008)
Observations	2532	2532	2532	2532	2532	2532
Within R-squared	0.507	0.888	0.526	0.739	0.893	0.913
Locality	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6) for Argentina. The dependent variable in columns (1) and (4) is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each locality at the bi-weekly level. The dependent variable in columns (2) and (5) is the average size of withdrawals and in columns (3) and (6) the dependent variable is the total ATM transactions. The independent variable is the logarithm of the total confirmed deaths over the last 14 days in locality i and period t. In columns (4)–(6) we control for the logarithm of total cash expenditures. We use Driscoll and Kraay standard errors with four lags. All the specifications include locality and time effects. The *** and **, represent statistical significance at 1% and 5% levels, respectively.

Appendix C: Chile

Table C1: Summary statistics – Comuna level (Chile).

	(1) Mean	(2) Std. Dev.	(3) Pct. 25	(4) Median	(5) Pct. 75
ATM transactions	22,940.02	83,756.93	7831.40	11,276.47	17,964.81
ATM disbursements	1,886,936	5,715,463	720,431	1,051,416	1,693,311
ATM disbursements per transaction	90.69	16.60	79.84	88.42	98.85
New COVID-19 cases (monthly)	2182.56	4127.08	205.14	467.57	1783.43
New COVID-19 deaths (monthly)	82.13	170.13	4.25	13.00	58.75

The table shows descriptive statistics of the variables of interest at the commune level (mean, standard deviation, percentile 25th, median, and percentile 75th) in the year 2020. The exchange rate used is the one that prevailed on January 1, 2020 (i.e. 1 Chilean Peso equals 0.0014 United States Dollar); all amounts are expressed in real dollars. The variables presented are daily averages, except those that relate to the COVID-19 pandemic. "New COVID-19 Cases" indicates the changes in the confirmed cases in a month at the commune level. "New COVID-19 Deaths" indicates the changes in the confirmed deaths in a 1 month at the commune level. The average of these variables is taken after the first case was confirmed on March 3rd, 2020.

Table C2: Cases and the use of cash: Chile.

	(1) $\text{Log}\,\frac{W}{N}$	(2) $\text{Log}\,W$	(3) $\text{Log}\,N$	(4) $\text{Log}\,\frac{W}{N}$	(5) $\text{Log}\,W$	(6) $\text{Log}\,N$
Log Cases(t)	0.049^{**}	0.010^{***}	-0.039^{**}	0.024^{***}	0.012^{***}	-0.012^{***}
	(0.015)	(0.002)	(0.012)	(0.005)	(0.002)	(0.002)
Log $C(t)$				-0.834^{***}	0.083^{*}	0.917^{***}
				(0.072)	(0.036)	(0.036)
Observations	1873	1873	1914	1873	1873	1873
Within R-squared	0.254	0.703	0.499	0.65	0.716	0.922
Commune	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6) for Chile. The dependent variable in columns (1) and (4) is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each commune at the monthly level. The dependent variable in columns (2) and (5) is the average size of withdrawals and in columns (3) and (6) the dependent variable is the total ATM transactions. The independent variable is the logarithm of the total confirmed cases over the last month in commune i and period t. In columns (4)–(6) we control for the logarithm of total expenditures paid in cash. We use Driscoll and Kraay standard errors with four lags. All the specifications include commune and time effects. The ***, **, and *, represent statistical significance at 1% and 10% levels, respectively.

Table C3: Deaths and the use of cash: Chile.

	(1) Log $\frac{W}{N}$	(2) Log W	(3) Log N	(4) Log $\frac{W}{N}$	(5) Log W	(6) Log N
Log Deaths(t)	0.005	0.001	−0.005	0.002	0.001	−0.001
	(0.004)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Log $C(t)$				-0.851^{***}	0.074^{*}	0.926^{***}
				(0.075)	(0.037)	(0.037)
Observations	1873	1873	1914	1873	1873	1873
Within R-squared	0.22	0.699	0.481	0.642	0.709	0.921
Commune	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y

The table reports the estimates of Eq. (6) for Chile. The dependent variable in columns (1) and (4) is the transaction cost of adjusting the stock of cash, which is approximated using the ratio of the daily average size of withdrawals and the daily average of the total ATM transactions for each commune at the monthly level. The dependent variable in columns (2) and (5) is the average size of withdrawals and in columns (3) and (6) the dependent variable is the total ATM transactions. The independent variable is the logarithm of the total confirmed deaths over the last month in commune i and period t. In columns (4)–(6) we control for the logarithm of total cash expenditures. We use Driscoll and Kraay standard errors with four lags. All the specifications include commune and time effects. The *** and *, represent statistical significance at 1% and 10% levels, respectively.

Appendix D: Mexico

We use the Financial Inclusion Database (BDIF) from the National Banking and Securities Commission (CNBV). The data consist of monthly data gathered from commercial banks and other financial entities related to financial inclusion. The databases include variables such as bank branches, ATMs, ATM transactions, and debit contracts.[24] Data set is disaggregated at the bank and municipality level and contains information on the number of bank branches that have closed due to the pandemic each time period. The data gathered for this paper corresponds to the period 2011–2020. Since we study the pandemic period, we focus on data from January to August 2020.

The average municipality in our data has 65,386 (std. 255,850) ATM transactions per month. It also has 4 banks, 5 bank branches, 26 ATMs. The table also reports the average changes in the confirmed cases and deaths in a month. Over our sample period, the average municipality suffered an increase of approximately 64 new confirmed cases per month.

Table D1: Summary statistics – municipality level (Mexico).

	(1) Mean	(2) Std. Dev.	(3) Pct. 25	(4) Median	(5) Pct. 75
ATM transactions	65,386.14	25,5850.70	0.00	2635.67	21,929.00
Banks	4.00	4.35	1.00	2.00	5.00
ATMs	26.28	117.95	0.00	1.00	7.00
Branches	5.07	19.49	0.00	0.00	2.00
Branches closed	0.75	3.63	0.00	0.00	0.00
New COVID-19 cases (monthly)	63.99	211.57	3.50	9.17	30.05
New COVID-19 deaths (monthly)	7.68	26.08	0.50	1.25	3.76

The table shows descriptive statistics of the variables of interest at the municipality level (mean, standard deviation, 25th percentile, median, and 75th percentile) in the year 2020. The variables presented are daily averages, except those that relate to the COVID-19 pandemic. "New COVID-19 Cases" indicates the changes in the confirmed cases in a month at the municipality level. "New COVID-19 Deaths" indicates the changes in the confirmed deaths in a month at the municipality level. The average of these variables is taken after the first case was confirmed on February 28th, 2020.

24 Since the information is reported by financial institutions to the CNBV, it does not include transactions at white-label ATMs.

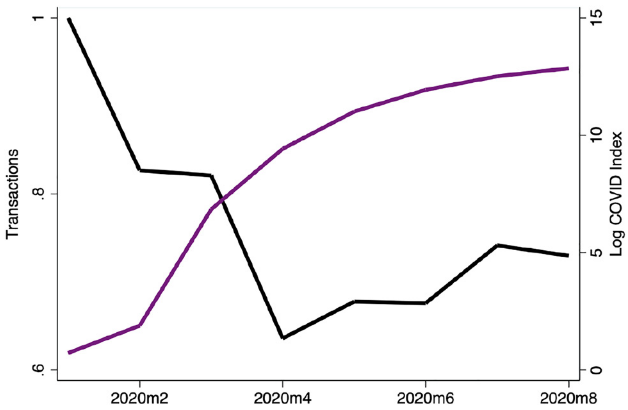

Figure D1: COVID-19 and the use of cash: Mexico.
The figure shows the evolution of ATM transactions normalized to 1 on January 2020 (black line) and the logarithm of COVID index (i.e. COVID index = $(\text{Cases})^{1/2}(\text{Deaths})^{1/2}$) in Mexico (purple line).

Table D2: COVID-19 and the use of cash: transactions (*N*) – Mexico.

	(1)	(2)	(3)	(4)
Log Cases(*t*)	−0.013* (0.005)			
Log Deaths(*t*)		−0.008* (0.004)		
Log COVID(*t*)			−0.012* (0.005)	
Log Branches Closed(*t*)				−0.097* (0.042)
Observations	32,167	32,167	32,167	41,300
Within *R*-squared	0.002	0.002	0.002	0.013
Bank-municipality	Y	Y	Y	Y
Time	Y	Y	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the logarithm of the total ATM transactions for each bank-municipality at the monthly level. The independent variable in column (1) is the logarithm of the total confirmed cases over the last month in a given municipality and period. In column (2) the independent variable is the total confirmed deaths over the last month. In column (3) the independent variable is COVID index $= (\text{Cases})^{1/2}(\text{Deaths})^{1/2}$, where Cases are the total confirmed cases in the municipality over the last month and Deaths are the total confirmed deaths over the last month in a given municipality and period. In column (4) the independent variable is the total branches closed due to COVID-19 for a given bank-municipality and period. We use Driscoll and Kraay standard errors. All the specifications include bank-municipality and time effects. The *, represent statistical significance at 10% level.

Table D3: Branches closed and the use of cash: transactions (*N*) – Mexico.

	(1)	(2)	(3)	(4)
Log Branches Closed(*t*)	−0.097***	−0.086***	−0.099***	−0.133***
	(0.015)	(0.015)	(0.016)	(0.019)
Observations	40,935	39,110	40,830	39,005
Within *R*-squared	0.001	0.001	0.001	0.002
Bank-county	Y	Y	Y	Y
Time	Y	N	N	N
County-time	N	Y	N	Y
Bank-time	N	N	Y	Y

The table reports the estimates of Eq. (6). The dependent variable is the logarithm of the total ATM transactions for each bank-municipality at the monthly level. The independent variable is the total branches closed due to COVID-19 for a given bank-municipality and period. The data is monthly at the bank-municipality level and comes from the National Banking and Securities Commission (CNBV). The standard errors are clustered at the municipality-time level. The ***, represent statistical significance at 1% level.

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