# Bank Risk-Taking and Impaired Monetary Policy Transmission*

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How does risk-taking affect the transmission of interest rate changes into loan issuance? We study this question in a banking model with agency frictions. The risk-free rate affects bank lending via a portfolio adjustment and a loan risk channel. The former implies that the bank issues more loans when the risk-free rate falls. The latter implies that the bank may issue fewer loans because lower risk-free rates lead to higher risk-taking. Thus, the loan risk channel can counteract the portfolio adjustment channel. There exists a reversal rate, so that loan supply even contracts due to higher risk-taking. The model's implications square with recent evidence on monetary transmission.

JEL Codes: G21, E44, E52.

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## 1. Introduction

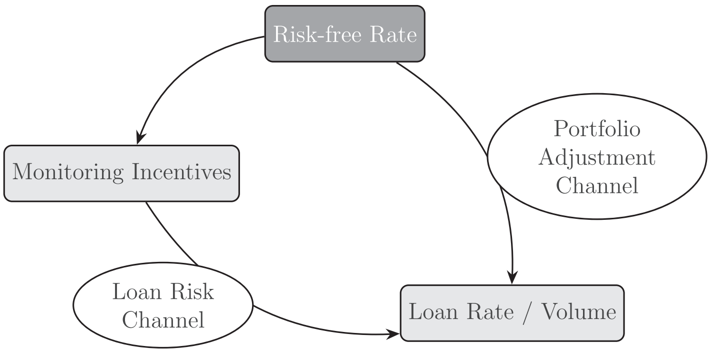
Central banks in several advanced economies have until recently kept their policy rates at historically low levels, often close to the zero lower bound. The extant literature has highlighted two key concerns on interest rate policies in such an environment. First, lower policy rates may induce banks to take more risks, which could pose a threat to financial stability (Borio and Zhu 2012). Second, lower rates could also depress bank profits to the point where banks respond less to additional monetary stimulus (Eggertsson et al. 2019) or even reduce the supply of credit to the economy (Brunnermeier, Abadi, and Koby 2023). Both phenomena have been studied in separate theoretical frameworks, but empirical evidence covering the recent period of low interest rates also suggests a close link between them, which is difficult to reconcile with existing models: the weakening of the transmission of policy rates correlates with an increase in riskier lending (Heider, Saidi, and Schepens 2019; Miller and Wanengkirtyo 2020; Arce et al. 2021).

In the present paper, we ask how such a link between impaired transmission and risk-taking can arise. We show that if deposit rates are bounded below and banks hold a sufficiently large share of fixed-income assets whose return changes with the risk-free rate, higher risk-taking and the impairment of monetary transmission can become "two sides of the same coin." In particular, if interest rates are at a sufficiently low level, further reductions of interest rates incentivize banks to increase risk-taking, which, in turn, weakens the transmission of policy rates into loan rates and loan volumes.

We consider a purposefully simple model of a penniless banker who uses deposits to fund the issuance of risky loans and the holdings of safe assets, such as bonds or central bank reserves. The banker can exert a monitoring effort to reduce the risk of default of her loan portfolio. Depositors can observe the loan issuance and the safe asset holdings of the banker. However, the monitoring effort is not observable (and hence uncontractible), thus creating an agency problem between the banker and her depositors.

In this setting, we study how changes in the risk-free rate affect loan rates and loan volumes. The transmission of the risk-free rate works via two channels, a direct portfolio adjustment channel and an indirect loan risk channel (see Figure 1).

**Figure 1. Direct Portfolio Adjustment Channel and Indirect Loan Risk Channel**




The portfolio adjustment channel reflects the conventional view of monetary transmission, which holds that lower risk-free rates are expansionary and translate into more bank lending. As in standard banking models, a lower risk-free rate reduces the return on safe assets and the opportunity cost of loan issuance. The banker, in turn, optimally issues more loans at lower loan rates (Freixas and Rochet 1997).

The indirect loan risk channel arises because changes in the risk-free rate also alter the banker's monitoring incentives, which, in turn, affect the banker's optimal loan issuance.[1] In particular, if monitoring incentives improve, loan risk declines and the banker optimally expands the issuance of loans by lowering the loan rate.

However, the risk-free rate exerts two opposing effects on monitoring incentives, implying that it is a priori not clear whether the loan risk channel amplifies or counteracts the portfolio adjustment channel. On the one hand, a lower risk-free rate reduces the profitability of safe assets and depresses expected profits. This *safe asset effect* worsens monitoring incentives. On the other hand, if the banker can pass on a lower risk-free rate to depositors, profits increase. This *deposit pass-through effect* improves monitoring

[1] We use the term "loan risk channel" to refer to the indirect effect of the risk-free rate on loan issuance via changes in monitoring incentives. Our loan risk channel should be distinguished from the "risk-taking channel," which refers to the direct effect of the risk-free rate on risk-taking incentives (Dell'Ariccia, Laeven, and Marquez 2014).

incentives. Whenever the safe asset effect dominates the deposit pass-through effect, the banker's monitoring incentives worsen, and her risk-taking increases when the risk-free rate becomes lower (and vice versa if the deposit pass-through effect dominates).

We show that the interaction between the portfolio adjustment channel and the loan risk channel can lead to three possible cases depending on the level of the risk-free rate.

First, if the risk-free rate is sufficiently high, the deposit pass-through effect dominates the safe asset effect, and the loan risk channel amplifies the portfolio adjustment channel. Second, for lower values of the risk-free rate, the safe asset effect dominates the deposit pass-through effect. The loan risk channel counteracts the portfolio adjustment channel. The banker still increases her loan issuance when the risk-free rate falls, but the increase in loan risk lessens her loan issuance. Third, if the risk-free rate is sufficiently low, the loan risk channel can even dominate the portfolio adjustment channel. In this case, further reductions in the risk-free rate lead the banker to reduce lending. The critical value below which the loan risk channel dominates the portfolio adjustment channel constitutes a reversal rate, as in Brunnermeier, Abadi, and Koby (2023). Like in their model, a precondition for the existence of a reversal rate is that bank profits decrease in the risk-free rate. In contrast to their model, the reversal rate in our model does not arise due to an exogenous constraint on future bank profits but stems from the agency friction between the banker and her depositors. We derive a simple condition for the occurrence of this "reversal scenario": the loan risk channel dominates the portfolio adjustment channel if the banker reduces her monitoring more than one-for-one in response to a reduction in the risk-free rate.

To simplify the exposition of the key mechanism behind the interaction of risk-taking and monetary policy transmission, we make two assumptions in our baseline model.

First, there is a lower bound on deposit rates; i.e., there exists a minimal return that the banker must offer on deposits for agents to be willing to hold them rather than switch to cash. This assumption reflects the empirical observation that changes in deposit rates become progressively smaller and approach a lower bound when policy rates are lowered towards negative territory (Eggertsson et al. 2019).

Second, the banker always holds a non-negligible amount of assets whose rate of return changes in lockstep with changes in the policy rate. We assume that these are "safe assets" such as central bank reserves, government bonds, or senior tranches of mortgage-backed securities.[2] For the safe asset effect to arise, the banker's expected profit must react sufficiently to changes in the risk-free rate. That is, the banker must be somewhat constrained in reducing her safe assets in order to mitigate (or even to offset completely) the negative effect of a lower risk-free rate on her profits. There are various reasons why banks face such constraints in practice. For example, due to setup and switching costs, deposits are a quasi-fixed factor of production (Flannery 1982; Sharpe 1997). Once banks raise deposit funding before deciding on their loan issuance, deposit and loan volumes are not necessarily completely balanced.[3] As a consequence, deposits in excess of what is required to fund loan issuance may be held as reserves with the central bank or invested in short-term fixed-income securities. In addition, banks face regulatory constraints, such as reserve or liquidity requirements, that force them to cover a certain share of their deposit liabilities with safe and liquid assets, like reserves or government bonds. Moreover, since the financial crisis of 2008/09, central banks have expanded reserves through asset purchase and lending programs beyond what is required by the banking sector in aggregate (Ennis and Wolman 2015; European Central Bank 2017; Bechtel et al. 2021). Under such a regime, individual banks may end up with excess reserves without being able to instantly dispose of reserves via the interbank market (Brandao-Marques et al. 2021).

To simplify the exposition in the baseline model, we follow Acharya and Naqvi (2012) and assume that the banker has a fixed amount of deposits and cannot adjust the "intensive margin" of her deposits. Moreover, we fix the deposit amount such that the banker

[2]We could also allow the banker to invest in risky fixed-income securities, provided that their payoffs are uncorrelated with the payoffs from the bank's loans and that a no-arbitrage condition ensures that their expected return matches the risk-free rate.

[3]In practice, banks often adjust deposit volumes by changing the rate offered on deposits. Empirically, in particular at low rates, rate adjustments and, by extensions, adjustments in deposit volumes, occur rather infrequently (Paraschiv 2013; Jobst and Lin 2016; Döpp, Horovitz, and Szimayer 2022), suggesting an imperfect adjustment between loans and deposits.

is bound to hold more deposits than what she needs to fund her optimal loan issuance. Any residual deposits are invested in safe assets whose return moves in lockstep with the risk-free rate. Put differently, although the banker can trade off loan issuance and safe assets at the margin, she cannot shrink her balance sheet by issuing fewer deposits and disposing of safe assets completely.

We consider several extensions of this baseline model to probe the robustness of its mechanism. First, we analyze the effect of insured deposits on the possibility of transmission reversal. Deposit insurance (if not fairly priced) provides an exogenous subsidy to the banker that increases her profits. As a consequence, deposit insurance mitigates the problem of transmission reversal. In the limit, when all deposits are insured, the reversal rate ceases to exist. Thus, ceteris paribus, a transmission reversal constitutes less of a problem for banks that are funded with a larger share of insured deposits.

Second, we relax the admittedly stark assumption that the banker cannot adjust the intensive margin of her deposits and the size of her balance sheet. Instead, we allow the banker to endogenously choose deposits and safe assets. We consider two variants of the model that both preserve the safe asset effect. In the first, we assume that the bank faces random inflows or outflows to depositors' accounts. These random changes to deposits are matched on the banker's balance sheet by inflows and outflows of central bank reserves. As a consequence, the bank may end up holding excess reserves with a certain probability. This extension illustrates that the presence or absence of the safe asset effect depends on the banker's ability to optimally adjust her safe asset position. In particular, we recover the results in the benchmark model if the probability of a deposit inflow (i.e., ending up with excess reserves) approaches unity, whereas the safe asset effect disappears if the probability of random reserve changes goes to zero. In the second variant, instead of random deposit flows, we assume that the banker faces a liquidity requirement that forces her to hold safe assets equal to a certain share of her deposits (as in Brunnermeier, Abadi, and Koby 2023). In this case, the portfolio adjustment and the loan risk channel always move in the same direction, but both switch signs once the safe asset effect dominates the deposit pass-through effect. The dominance of the safe asset effect becomes a necessary and sufficient condition for the reversal of monetary transmission.

**Related Literature.** Our paper relates to a large body of literature that analyzes the transmission of monetary policy through the banking sector. The traditional view is that a reduction in policy rates reduces banks' funding cost and induces greater loan supply (Bernanke and Blinder 1988; Bernanke and Gertler 1995; Kashyap and Stein 1995). A variant of this channel is at work in our model, but we show that it can be weakened or amplified by an (a priori) ambiguous indirect loan risk channel that arises from the agency problem between the bank and its depositors.

The loan risk channel connects our paper to the literature on the risk-taking channel of monetary policy (e.g., Dell'Ariccia, Laeven, and Marquez 2014; Martinez-Miera and Repullo 2017). The risk-taking channel refers to the direct effect of interest rate changes on the bank's monitoring incentives. We show how the presence of a lower bound on deposit rates and the presence of safe asset holdings creates a novel variant of the risk-taking channel. However, the focus of our model is on the loan risk channel, i.e., the indirect effect of the risk-free rate on loan issuance via monitoring incentives.

The banks in our model face an agency problem similar to that of Dell'Ariccia, Laeven, and Marquez (2014). In contrast to Dell'Ariccia, Laeven, and Marquez (2014), who focus on the effect of leverage, we adopt the assumption of a fixed deposit volume from Acharya and Naqvi (2012) to concentrate on the effect of monetary policy on the bank's endogenous portfolio adjustment between loans and safe assets. Our model therefore complements Dell'Ariccia, Laeven, and Marquez (2014) in two ways. Firstly, in contrast to their results, even a fully leveraged bank can increase risk-taking in response to a lower policy rate because of the interaction between the deposit pass-through and the safe asset effect. Secondly, the effect of the risk-free rate on loan rates depends on the interaction between the portfolio adjustment and the loan risk channel. This decomposition allows us to show how the transmission of policy rates can become weaker at low levels of the policy rate.[4]

The dependency of monetary transmission on the level of the policy rate connects our paper to the growing literature on monetary

[4] In Dell'Ariccia, Laeven, and Marquez (2014), the total effect of interest rates on loan rates is unambiguously positive, so that a reversal of transmission cannot arise.

policy transmission in a low interest rate environment. Eggertsson et al. (2019) argue that the increasing attractiveness of cash impairs the pass-through to deposit rates when the policy rate approaches the zero lower bound or becomes negative. Brunnermeier, Abadi, and Koby (2023) show the existence of the reversal rate below which further reductions in policy rates lead to an increase in loan rates. Eggertsson et al. (2019) and Brunnermeier, Abadi, and Koby (2023) derive their results by imposing an exogenous net worth constraint that mechanically increases equilibrium loan rates. Darracq Pariès, Kok, and Rottner (2020) study the reversal rate in a general equilibrium model with agency frictions. Their net worth constraint arises because the banker can abscond with deposits. Our model complements these papers by showing how a reversal rate can arise from an agency problem and the bank's risk-taking incentives.

Several recent papers analyze the effects of excess reserves on the determination of the price level (Ennis 2018) or the effect of bank lending (Martin, McAndrews, and Skeie 2016). Our results complement Martin, McAndrews, and Skeie (2016). They argue that reserve holdings do not matter for bank lending in a frictionless economy, but they do so in the presence of balance sheet costs. We show how excess reserves affect lending in the presence of agency frictions.

The implications of our model are in line with empirical observations at low levels of the policy rate, such as a positive relationship between bank profits and policy rates (Ampudia and Van den Heuvel 2022; Wang et al. 2022), or a negative relationship between mortgage rates and policy rates (Basten and Mariathasan 2020; Miller and Wanengkirtyo 2020). Our model suggests an explanation for higher risk-taking at rock-bottom interest rates (Heider, Saidi, and Schepens 2019; Basten and Mariathasan 2020; Bittner, Bonfim, et al. 2021), and shows why the pass-through to loans may weaken specifically for riskier banks (Arce et al. 2021).

## 2. Model Setup

We consider a bank over two periods, indexed by $t = 0, 1$. The bank is run by a penniless risk-neutral bank owner/manager ("banker"). The banker can obtain deposits from a large number of risk-neutral depositors. The banker decides on the issuance of loans and on the monitoring of her loans. Monitoring entails a private cost for the banker and reduces the riskiness of her loans. Depositors cannot observe the banker's monitoring choice and the banker cannot commit to a certain level of monitoring. The main focus of our analysis is on the transmission of monetary policy to loan rates, the loan volume, and the loan risk. We take the gross risk-free interest rate $r > 0$ as the measure of monetary policy and assume that it can be perfectly controlled by the central bank.

**Bank Liabilities.** The banker raises deposits in period 0. Deposits are uninsured and depositors must be compensated for the risk that the banker cannot fully repay depositors in period 1.[5] Thus, to attract deposits, the banker must offer a deposit rate, $r_D$, which, in expected terms, matches the depositors' outside option, $u(r)$.

ASSUMPTION 1. *The depositors' outside option $u(r) \geq r$ is bounded below by $\underline{u}$, i.e., $u(r) = \underline{u}$ for all $r \leq u^{-1}(\underline{u})$. For $r > u^{-1}(\underline{u})$, $u(r)$ is continuously increasing and convex; moreover, $u'(r)$ is continuous at $u^{-1}(\underline{u})$, i.e., $u'(r)$ satisfies* $\lim_{r \downarrow u^{-1}(\underline{u})} u'(r) = 0$.

The lower bound $\underline{u}$ reflects the idea that depositors would switch to other assets, such as non-interest-bearing cash holdings, once the risk-free rate becomes too low. The lower bound is not necessarily equal to zero, as negative rates could still be compensated for in the form of non-pecuniary benefits of deposits, such as the safety and ease of making payments. The lower bound on $u(\cdot)$ is the key assumption needed for the mechanism of our model, whereas the continuity and convexity assumptions are made for the sake of technical tractability and can easily be dropped (see Section 4.3).

To further simplify the exposition of the model, we assume that the banker cannot adjust the "intensive margin" of her deposits. That is, she either raises an amount $D$ or no deposits at all. We relax this assumption in Section 4.2 where we allow the banker to choose deposits endogenously.

ASSUMPTION 2. *The amount of deposits, $D$, is exogenously given.*

**Bank Assets and Monitoring.** The banker is a monopolist in the local loan market. The demand for loans in period 0 is described

[5] Section 4.1 considers the effect when the banker also issues insured deposits.

by a demand curve $L(r_L)$, with $L'(r_L) < 0$ and $L''(r_L) \leq 0$, where $r_L$ denotes the gross interest rate the banker charges on loans.

Loans are risky and are repaid in period 1 with probability $q \in (0, 1)$. The banker can exert unobservable monitoring effort to influence the repayment probability of her loans. We assume that monitoring translates one-to-one into the repayment probability, i.e., the banker can choose $q$ directly. Monitoring involves a private cost[6]

$$c(q) = \frac{\kappa}{2} q^2, \quad \text{where } \kappa > 0.$$

Alternatively, the banker can invest in a risk-free asset that yields the gross risk-free return $r$ in period 1. One can think of the risk-free asset as government bonds or reserves held with the central bank.[7] The amount invested in the risk-free asset is denoted by $R$.

The bank's funding constraint in period 0 is given by

$$R + L = D. \tag{1}$$

The amount invested in the risk-free asset is determined endogenously through the banker's choice of loans as the residual $R = D - L$. Henceforth, we use $\rho \equiv \frac{R}{D} = 1 - \frac{L}{D}$ to denote the share of deposits held in the risk-free asset.

We simplify the exposition of the model by imposing the following assumption on the relationship between loan issuance and the fixed deposit volume.

Assumption 3. *The elasticity of the loan demand function,* $\eta(r_L) \equiv -\frac{L'(r_L) r_L}{L(r_L)}$, *satisfies*

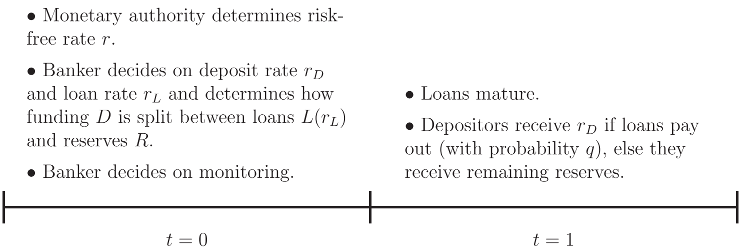
$$\eta(L^{-1}(D)) < 1.$$

Assumption 3 implies that the banker never exhausts her entire funding base to issue loans, but always holds a strictly positive

[6]For analytical tractability, we assume that monitoring costs do not depend on the banker's loan issuance. For example, $c(q)$ may represent setup costs for risk-management systems that, once in place, can be used to process a large number of loans. As we show in Appendix A.2, our results remain qualitatively unchanged if we assume a cost function that scales with the loan volume, $c(q, r_L) = \frac{\kappa}{2} q^2 L(r_L)$.

[7]The asset can be risky as long as its payoffs are not correlated with the bank loan risk and a no-arbitrage condition holds so that the asset's expected return equals the risk-free rate.

**Figure 2. Sequence of Events**




amount of safe assets. We relax Assumption 3 together with Assumption 2 in Section 4.2.

**Sequence of Events and Equilibrium.** Figure 2 shows the sequence of events in the model. An equilibrium of the model is given by a loan rate $r_L^*$ and a deposit rate $r_D^*$, which jointly determine the bank's optimal loan supply, $L^*$, optimal safe asset holdings, $R^*$, and the monitoring choice, $q^*$. The loan rate $r_L^*$ and the monitoring choice $q^*$ maximize the banker's expected profits given the funding constraint (1), while the deposit rate $r_D^*$ ensures depositor participation, given depositors' rational expectations about the bank's monitoring choice.

## 3. The Portfolio Adjustment and the Loan Risk Channel

**Optimal Monitoring Choice.** We solve the model backwards by first considering the banker's optimal choice of monitoring and then determining her optimal loan issuance. The banker's expected profits, for given $r_L$ and $R$, can be written as

$$\Pi = q\left(r_L L(r_L) + rR - r_D D\right) - \frac{\kappa q^2}{2}. \tag{2}$$

The first-order condition for the optimal monitoring choice becomes[8]

$$r_L L(r_L) + rR - r_D D - \kappa \hat{q} = 0. \tag{3}$$

[8] All derivations can be found in the appendix.

Given that depositors rationally anticipate the bank's optimal monitoring choice $\hat{q}$, the interest rate on deposits that ensures depositor participation must satisfy

$$\hat{q}r_D + (1-\hat{q})\frac{rR}{D} \geq u(r). \tag{4}$$

Depositors expect to be paid $r_D$ with probability $\hat{q}$. With converse probability, the bank defaults when loans do not pay out at maturity, and depositors obtain a senior claim over a pro rata share of the remaining safe assets. The expected repayment to the depositors must be at least as large as their outside option $u(r)$. Since the banker's expected profits are strictly decreasing in $r_D$, condition (4) binds at the optimum, so we can substitute

$$r_D = \frac{u(r) - (1-\hat{q})\frac{rR}{D}}{\hat{q}} \tag{5}$$

into condition (3) and solve for the optimal monitoring choice $\hat{q}$.[9]

LEMMA 1. *The banker's optimal monitoring choice is given by a function $\hat{q}(r_L, r)$ with*

$$\frac{\partial \hat{q}}{\partial r_L}\begin{cases} \geq 0 & \text{if } \frac{\hat{q}r_L - r}{\hat{q}r_L} \leq \frac{1}{\eta(r_L)} \\ < 0 & \text{else} \end{cases} \quad \text{and} \quad \frac{\partial \hat{q}}{\partial r}\begin{cases} \geq 0 & \text{if } u'(r) \leq \rho \\ < 0 & \text{else} \end{cases},$$

*where $\eta(r_L) \equiv -L'(r_L)r_L/L(r_L)$ denotes the loan demand elasticity and $\rho \equiv R/D$.*

The effects of $r_L$ and $r$ on the optimal monitoring level reflect the effects of these rates on the banker's expected profits. Whenever a marginal increase in these rates raises profits, the banker increases her monitoring and vice versa.

More specifically, a higher loan rate increases monitoring whenever the loan rate $r_L$ is such that the Lerner index, $(\hat{q}r_L - r)/\hat{q}r$, is

[9] The equation that pins down $\hat{q}$ is quadratic and has two solutions. Following Allen, Carletti, and Marquez (2011), we choose the larger of the two roots. Moreover, as Dell'Ariccia, Laeven, and Marquez (2014), we focus on the interior solution where $\hat{q} < 1$ and abstract from the corner solution where $\hat{q} = 1$. There is a sufficiently large range of values for $\kappa$ such that the interior solution exists.

lower than the inverse loan demand elasticity, $1/\eta(r_L)$, which is the standard condition for the profits of a monopolistic bank to (locally) increase in $r_L$ (Freixas and Rochet 1997).

Whether a lower risk-free rate increases profits and leads to higher monitoring depends on the relative magnitude of two effects. On the one hand, a marginal reduction in the risk-free rate lowers the value of the depositors' outside option and thereby reduces the banker's expected deposit funding costs. This *deposit pass-through effect* increases profits by an amount $u'(r)D$ and incentivizes the banker to increase monitoring. On the other hand, a marginal reduction in the risk-free rate reduces the banker's return on safe assets. This *safe asset effect* reduces profits by $R$ and induces the banker to reduce monitoring. Thus, a lower risk-free rate decreases monitoring if the deposit pass-through effect is smaller than the safe asset effect, i.e., if

$$u'(r)D < R \iff u'(r) < \rho. \tag{6}$$

**Optimal Loan Issuance and Reserve Holdings.** Substituting the funding constraint (1), the deposit rate (5), and the banker's optimal monitoring choice $\hat{q}(r_L, r)$ into (2) allows us to rewrite expected profits as

$$\Pi = \underbrace{\hat{q}(r_L, r) r_L L(r_L)}_{\text{Expected earnings on loans.}} + \underbrace{r(D - L(r_L))}_{\text{Earnings on reserves}} - \underbrace{u(r)D}_{\text{Cost of funds}} - \underbrace{\frac{\kappa}{2}\hat{q}(r_L, r)^2}_{\text{Monitoring cost}}. \tag{7}$$

The banker's remaining choice variable is the loan rate $r_L$. The optimal loan rate, $r_L^*$, is determined by the standard condition for loan issuance of a monopolistic bank: the Lerner index equals the inverse loan demand elasticity

$$\frac{\hat{q}(r_L^*, r) r_L^* - r}{\hat{q}(r_L^*, r) r_L^*} = \frac{1}{\eta(r_L^*)}. \tag{8}$$

At the optimum point, the elasticity of the loan demand exceeds unity, $\eta(r_L^*) > 1$. Condition (8) takes this particularly simple form because the effect of $r_L$ on $\hat{q}$ can also be expressed in terms of the Lerner index and the inverse demand elasticity (cf. Lemma 1).

**Monetary Policy Transmission.** Monetary policy actions that change the risk-free rate affect the banker's optimal loan rate (and therefore the loan volume) through a *portfolio adjustment channel* and a *loan risk channel:*

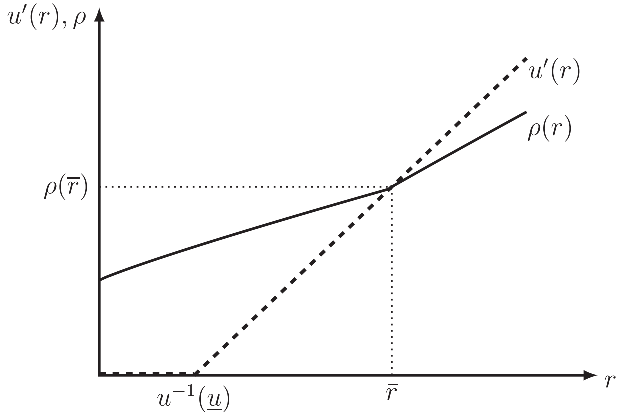
$$\frac{dr_L^*}{dr} = \underbrace{\overbrace{\frac{\partial r_L^*}{\partial r}}^{(+)}}_{\substack{\text{portfolio adjustment} \\ \text{channel}}} + \underbrace{\overbrace{\frac{\partial r_L^*}{\partial q}}^{(-)} \times \overbrace{\frac{\partial \hat{q}(r_L^*, r)}{\partial r}}^{(+)/(-)}}_{\text{loan risk channel}}. \tag{9}$$

The conventional view of monetary policy transmission holds that a lower risk-free rate is expansionary because it induces an increase in bank loan issuance. The portfolio adjustment channel reflects this conventional transmission of monetary policy. Effectively, the banker solves an optimal portfolio problem by allocating her funds between two investment opportunities (loans and safe assets).[10] Given $\hat{q}$, a lower risk-free rate reduces the opportunity cost of investing in loans rather than safe assets. As a consequence, the banker optimally reduces the loan rate and increases the amount of loan issuance.

In contrast to the portfolio adjustment channel, the effect of the loan risk channel is ambiguous: it can either amplify or dampen the portfolio adjustment channel. To understand the intuition behind the workings of the loan risk channel, note that, ceteris paribus, a lower success probability increases the loan rate and reduces the amount of loan issuance, i.e., $\partial r_L^*/\partial q < 0$. The reason is that the bank optimally reacts to a lower success probability by increasing the loan rate in order to keep the expected marginal benefit from issuing an additional loan equal to the risk-free rate that it earns on safe assets (cf. Equation (8)). Thus, whenever the safe asset

[10]Since the volume of deposits is fixed, the optimal loan rate is independent of the costs of deposits as in the textbook version of a monopolistic bank with separable loan and deposit choices (Freixas and Rochet 1997). In Section 4.2, we show two variants of the model where the banker can choose the deposit volume.

**Figure 3. Required Marginal Deposit Rate, $u'(r)$, and Reserves-Deposit Ratio, $\rho$**




**Note:** To the right (left) of $\overline{r}$, the loan risk channel amplifies (weakens) the portfolio adjustment channel, as can be seen from the change in the slope of the red curve at $\overline{r}$.

effect dominates, a reduction in the risk-free rate reduces monitoring, $\partial\hat{q}/\partial r > 0$, and the loan risk channel counteracts the portfolio adjustment channel, thus weakening monetary transmission.

Proposition 1. *For a sufficiently small risk-free rate, the safe asset effect dominates the deposit pass-through effect and the loan risk channel weakens the transmission of monetary policy via the portfolio adjustment channel, i.e., there exists $\overline{r}$ such that*

$$r < \overline{r} \Rightarrow \frac{\partial\hat{q}}{\partial r} > 0. \tag{10}$$

Figure 3 illustrates Proposition 1. Note that the lower bound on $u(r)$ implies that for $r < u^{-1}(\underline{u})$, the deposit pass-through becomes fully impaired, i.e., $u'(r) = 0$. At this level of the risk-free rate, the banker is unable to pass a lower risk-free rate through to her depositors and she becomes unable to further reduce her expected funding costs. The dashed curve in Figure 3 shows the marginal required deposit rate, $u'(r)$, which becomes flat below $u^{-1}(\underline{u})$ when the pass-through is fully impaired. However, by Assumption 3, the banker always holds a strictly positive level of reserves, even at low risk-free rates below $u^{-1}(\underline{u})$. Thus, the safe asset effect dominates the deposit pass-through effect whenever the risk-free rate falls below $\overline{r} > u^{-1}(\underline{u})$. The solid curve shows the ratio of safe assets to deposits, evaluated at the optimal loan rate, $\rho(r) = 1 - L(r_L^*(r))/D$. For $r$ above the critical value $\overline{r}$, the loan risk channel amplifies the portfolio adjustment channel. Below the critical value $\overline{r}$, a lower risk-free rate reduces the banker's monitoring incentives, and the loan risk channel weakens the portfolio adjustment channel.[11] The slope of the ratio of safe assets to deposits becomes less steep when $r < \overline{r}$. The reason is that, due to the counteracting loan risk channel, the interest rate reduction required to achieve a given reduction in safe assets (a given increase in loan issuance) becomes larger.

**Reversal of Monetary Transmission.** The loan risk channel may not only weaken the portfolio adjustment channel; it can also dominate it. In this case, a lower risk-free rate leads to an *increase* in the loan rate and a *reduction* in the bank's loan supply.

PROPOSITION 2. *The loan risk channel dominates the portfolio adjustment channel, i.e.,* $\frac{dr_L^*}{dr} < 0$*, if and only if*

$$\frac{\partial \hat{q}(r_L^*, r)}{\partial r} \frac{r}{\hat{q}(r_L^*, r)} > 1. \tag{11}$$

To understand the intuition behind Proposition 2, recall that, on the one hand, a lower success probability makes loan issuance relatively less profitable compared to holding safe assets, implying that the bank cuts back its loan issuance when $q$ is lower. On the other hand, a lower risk-free rate reduces the return on safe assets and makes holding safe assets less profitable. If the reduction in the risk-free rate lowers the success probability and the profitability of loans by more than the profitability of reserves, the bank prefers to hold more safe assets, despite the lower risk-free rate. However, for the profitability of loans to fall by more than the profitability of safe

[11] Observe that condition (10) is only a sufficient condition. It does not rule out the possibility that the safe asset effect dominates the deposit pass-through effect at a higher level of the risk-free rate (above $\overline{r}$). Whether such a case can arise depends on the other properties of $u(r)$ and $L(r_L)$, such as the curvature or magnitude of its rate of change.

assets, the banker's monitoring must react strongly enough, i.e., a reduction in $r$ must lead to an overproportional reduction in $\hat{q}$.

PROPOSITION 3. *If monitoring costs are sufficiently high, then the loan risk channel dominates the portfolio adjustment channel if the risk-free rate becomes sufficiently low: that is, for $\kappa > \underline{\kappa}$, there exists a critical value $\hat{r} < \bar{r}$ such that*

$$r < \hat{r} \;\Leftrightarrow\; \frac{dr_L^*}{dr} < 0.$$

*The critical value $\hat{r}$ is strictly increasing in the bank's monitoring cost $\kappa$.*

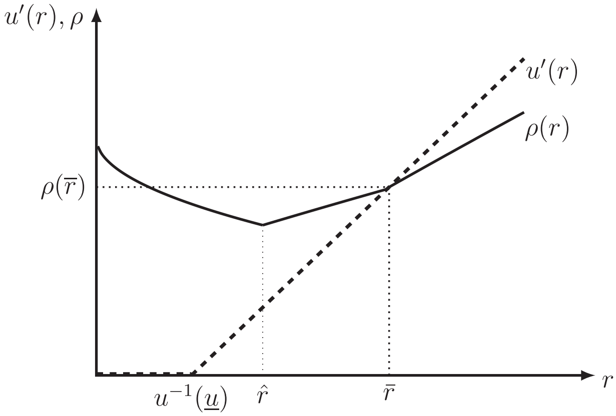
Proposition 3 translates the condition in Proposition 2 into a critical value for the risk-free rate. In particular, whenever the monitoring costs are sufficiently high and the risk-free rate falls below the critical rate, the elasticity of $\hat{q}$ becomes sufficiently large so that the loan risk channel becomes the dominant transmission channel of monetary policy. As in Brunnermeier, Abadi, and Koby (2023), below $\hat{r}$, reductions in the risk-free rate are contractionary rather than expansionary and $\hat{r}$ constitutes a *reversal rate.*

Figure 4 illustrates Proposition 3. As in Figure 3, it plots the required marginal deposit rate $u'(r)$ (dashed curve) against the ratio of safe assets to deposits, $\rho$ (solid curve). However, in Figure 4, we assume that $\kappa > \underline{\kappa}$, so that the reserves-deposit ratio becomes downward sloping for values of $r$ below the reversal rate $\hat{r}$. Since the reversal rate is equal to the point at which the loan risk channel just offsets the portfolio adjustment channel, it follows that the reversal rate must be strictly below the threshold $\bar{r}$.

Figure 5 summarizes our results by illustrating how the transmission of *changes* in the risk-free rate in our model depends on the prevailing *level* of the risk-free rate.

Our analysis complements Brunnermeier, Abadi, and Koby (2023) by showing that a reversal rate can arise as a consequence of banks' risk-taking behavior. The reversal rate in their model arises due to a binding exogenous constraint on future profits, whereas the reversal in our model is a consequence of the banker's endogenous risk choice that only exists if the banker increases her risk-taking sufficiently strongly in response to a change in the risk-free rate. The

**Figure 4. Reversal of Transmission when $\boldsymbol{\kappa} > \overline{\boldsymbol{\kappa}}$**




**Note:** For $r \in (\hat{r}, \overline{r})$, the loan risk channel weakens the portfolio adjustment mechanism. For $r < \hat{r}$, the loan risk channel dominates and monetary transmission reverses.

**Figure 5. Monetary Transmission and the Risk-Free Rate**

| transmission reversal | weakened transmission | strong transmission |
|---|---|---|
| $\frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} > 1$, $\frac{dL^*}{dr} < 0$ | $0 < \frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} < 1$, $\frac{dL^*}{dr} > 0$ | $\frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} < 0$, $\frac{dL^*}{dr} > 0$ |

$\hat{r}$ $\qquad$ $\overline{r}$

**Note:** The transmission of *changes* in the risk-free rate depends on the prevailing *level* of the risk-free rate. For $r > \overline{r}$, a lower risk-free rate, $r$, reduces risk-taking and raises loan issuance. For $r \in [\hat{r}, \overline{r}]$, a lower $r$ raises risk-taking and weakens loan issuance. For $r < \hat{r}$, risk-taking is too strong and transmission into loans reverses.

reversal rate in our model is just the most extreme manifestation of the more general phenomenon that the loan risk channel weakens monetary transmission for sufficiently low risk-free rates.

**Implications of the Model.** We use Propositions 1 and 3 to derive several testable implications from our model.

HYPOTHESIS 1. *An increase in the banker's exogenous deposit funding is associated with*

- *higher safe asset holdings, higher loan rates, and a lower loan volume;*
- *higher bank risk-taking;*
- *weaker monetary policy transmission.*

Hypothesis 1 follows because an increase in the deposit volume strengthens the safe asset effect compared to the deposit pass-through effect. As a consequence, the threshold $\bar{r}$ increases, and the range of policy rates at which the loan risk channel weakens the transmission via the portfolio channel becomes larger.

Hypothesis 1 is in line with recent empirical findings of Jimenez et al. (2012), Miller and Wanengkirtyo (2020), and Bittner, Rodnyansky, et al. (2021). Note first that an increase in deposits leads to an increase in safe asset holdings, e.g., in the form of excess reserves with the central bank or government bonds. Jimenez et al. (2012) show that banks with more liquidity on their balance sheet expand the issuance of loans less after a rate cut. However, they do not distinguish between required reserves and excess reserves. Miller and Wanengkirtyo (2020) show that, following a reduction in the policy rate, banks with larger excess reserves extend lending to riskier borrowers. Bittner, Rodnyanski, et al. (2021) further provide evidence that in the presence of a zero lower bound on deposit rates, banks that depend more on deposit funding and have greater exposure to large-scale asset purchases lend relatively less and increase their risk-taking more.

HYPOTHESIS 2. *The reversal rate is larger if, ceteris paribus,*

- *the bank has more deposits;*
- *the bank is riskier, and its loan portfolio is more costly to monitor.*

Hypothesis 2 follows from the effects of leverage, and the monitoring cost parameter, $\kappa$, on the reversal rate $\hat{r}$ (cf. Proposition 3). Higher deposits (and a larger cost parameter $\kappa$) exacerbate the agency conflict and increase the banker's risk-taking incentives. Since higher risk-taking raises the loan rate for any value of $r$, the reversal rate (at which the loan risk channel offsets the portfolio channel) also increases.

Hypothesis 2 is in line with recent evidence by Arce et al. (2021), who show that a negative correlation between policy rate and loan rates can be found for banks that are poorly capitalized and whose lending is riskier. Similarly, Basten and Mariathasan (2020) and Miller and Wanengkirtyo (2020) find that lower policy rates are negatively correlated with mortgage rates, but not with interest rates on other types of loan. Hypothesis 2 is consistent with these findings to the extent that mortgage handling is relatively more costly than the origination and handling of other types of loans.

## 4. Extensions and Discussion

### *4.1 Insured Deposits*

In this section, we consider how deposit insurance alters the transmission of monetary policy via portfolio adjustment and loan risk channels and the possibility of a transmission reversal. Suppose that a share $\delta \in [0,1]$ of deposits is insured at a flat rate normalized to zero. For simplicity, insured depositors have the same outside option as uninsured depositors.[12]

As before, we solve the model backward by first deriving the banker's optimal monitoring choice and thereafter the optimal loan rate. The first-order condition for the monitoring choice is as in Equation (3), except that we replace the deposit rate $r_D$ with the average deposit rate $\bar{r}_D$ which depends on the share of insured deposits. As uninsured depositors rationally anticipate bank monitoring $\hat{q}$, the average deposit rate is[13]

$$\bar{r}_D = \frac{(\delta\hat{q} + 1 - \delta)u(r) - (1-\delta)(1-\hat{q})\frac{rR}{D}}{\hat{q}}.$$

Substituting $\bar{r}_D$ into Equation (3) implicitly defines the banker's optimal monitoring $\hat{q}(r_L, r, \delta)$. Importantly, the condition for $\hat{q}$ to increase in $r$ is the same as in Lemma 1,

[12]Our results remain qualitatively unchanged if insured and uninsured depositors have different outside options. We discuss this case in Appendix A.3.

[13]For simplicity, we assume that, after default at maturity, the bank's cash flows from reserves are split on a pro rata basis among all depositors, insured and uninsured.

$$\frac{\partial \hat{q}(r_L, r, \delta)}{\partial r} > 0 \Leftrightarrow u'(r) < \rho.$$

An increase in $\delta$ increases monitoring: $\frac{\partial \hat{q}}{\partial \delta} > 0$. This "charter value effect" of deposit insurance is described in Cordella, Dell'Ariccia, and Marquez (2018). Because the deposit rate is given when the banker chooses her monitoring, a higher share of insured deposits amounts to a greater implicit subsidy from the deposit insurance, thereby reducing the repayments to depositors and increasing the banker's profits. As a consequence, higher deposit insurance coverage strengthens monitoring incentives.[14]

The banker's expected profit takes the same form as before in Equation (7) except that the implicit subsidy from funding with a share $\delta$ of insured deposits is added. Substituting the average deposit rate and the optimal monitoring choice into the expected profits yields

$$\Pi = \hat{q}(r_L, r)L(r_L) + rR - (u(r)D) - \frac{\kappa \hat{q}(r_L, r)^2}{2} + S(\delta, r_L, r, R),$$

where $S(\delta, r_L, r, R) \equiv \delta(1 - \hat{q}(r_L, r, \delta))(u(r)D - rR)$ is the implicit subsidy from the deposit insurance. The subsidy is equal to the part of insured deposit funding costs that has to be covered by the deposit insurance in case of bank default. As can be seen from the expression for $S(\cdot)$, an increase in $R$ reduces the implicit subsidy. This is because the deposit insurance can rely on a larger amount of safe assets to cover (part of) its liabilities in case the loans fail.

The transmission of monetary policy works as before through the portfolio adjustment and loan risk channels. Since optimal monitoring increases in the risk-free rate whenever the safe asset effect dominates the deposit pass-through effect, the condition for the loan risk channel to weaken monetary transmission remains formally the same as in the benchmark model with $\delta = 0$.

However, the presence of insured deposits changes the relative importance of the portfolio adjustment and loan risk channels in the transmission of monetary policy.

[14] Cordella, Dell'Ariccia, and Marquez (2018, Proposition 1) show that the charter value effect occurs if the share of deposit liabilities that are priced "at the margin" is sufficiently small. This is the case for our specification because we abstract from such deposits entirely.

PROPOSITION 4. *Given a share $\delta$ of insured deposits, the loan risk channel dominates the portfolio adjustment channel, i.e.,* $\frac{dr_L^*}{dr} < 0$, *if and only if*

$$\frac{\partial \hat{q}(r_L^*, r, \delta)}{\partial r} \frac{r}{\hat{q}(r_L^*, r, \delta)} > 1 + \frac{\hat{q}(r_L^*, r, \delta)\delta}{1-\delta}.$$

Comparing Propositions 2 and 4 shows that the condition for the dominance of the loan risk channel is stronger when the banker is funded with insured deposits. The reason is that the banker obtains a larger implicit subsidy from deposit insurance when she holds fewer safe assets. This asset substitution motive provides an additional incentive for the banker to increase her loan issuance when the risk-free rate falls. Thus, deposit insurance strengthens the portfolio channel and alleviates the problem of transmission reversal. Simply put, the deposit insurance subsidy mitigates the adverse effect of lower rates on the bank's profitability by increasing its profits.

HYPOTHESIS 3. *The reversal rate $\hat{r}$ is smaller for banks that are funded with a larger share of insured deposits. In the limit for $\delta \to 1$, the reversal rate ceases to exist.*

### *4.2 Endogenous Deposit Choice, Deposit Shocks, and Liquidity Requirements*

In this section, we briefly discuss the consequences of relaxing Assumptions 2 and 3 for our main results. In the benchmark model, the fixed amount of deposits (Assumption 2) determines the bank's balance sheet length and Assumption 3 implies that the bank holds a strictly positive amount of safe assets whose rate of return, in contrast to the loan rate, cannot be controlled by the banker. These assumptions ensure that the banker is exposed to the safe asset effect so that reductions in the risk-free rate can reduce her expected profits and lead to higher risk-taking and lesser loan issuance.

We now dispense with Assumption 2, i.e., we allow the banker to endogenously choose the amount of deposits and we consider two alternatives to Assumption 3. Under both alternatives, the banker continues to be exposed to the safe asset effect. First, we consider exogenous liquidity shocks to deposits, i.e., exogenous inflows and outflows to and from the depositors' accounts that randomly change the bank's end-of-period safe asset holdings. Second, we consider an exogenously imposed liquidity requirement, akin to the Basel regulations' liquidity coverage ratio (LCR).

It is worth pointing out that in the absence of these or other alternative assumptions, the banker in our model would have no incentives to hold safe assets. Absent the safe asset effect, the loan risk channel would always work into the same direction as the portfolio adjustment channel.

**Deposit Shocks.** We begin by considering a variant of the model where the bank can choose its deposits at the beginning of date 0. However, depositors are subject to a liquidity shock at the start of date 1, i.e., they face inflows and outflows to and from their deposit accounts. We assume that the bank cannot invest additional deposits in $t = 1$ into loans so that deposit flows must be balanced by an equivalent change in safe assets.[15]

To rule out precautionary motives for holding safe assets, we assume that the bank can access the central bank's standing deposit and lending facilities at an interest rate $r$ to deposit excess reserves or to cover deposit outflows and reserve shortfalls.[16]

Furthermore, we assume that the bank can also borrow ex ante from the central bank up to a fraction $\sigma \in (0, 1)$ of its loan issuance, i.e., we impose $R \geq -\sigma L$.

Liquidity shocks, denoted $x$, are proportional to deposits, $D$, and are drawn from a continuous distribution $F(\cdot)$ and with density $f(\cdot)$ over support $[-1, z]$. $zD$ is the maximal inflow to an individual deposit account. We assume that the liquidity shocks realize after the bank has contracted the deposit rate, set its loan rate, and has chosen the optimal monitoring effort. Without loss of generality, we set $\mathbf{E}[x] = 0$.

As before, we solve the model backwards. Given $r_D$, the optimal monitoring of the bank is still determined by Equation (3). The random inflows and outflows to deposit accounts affect the deposit cost

[15]Inflows to deposit accounts automatically add to the bank's central bank reserves. Outflows from deposit accounts need to be covered by running down reserves or by additional borrowing from the central bank.

[16]Allowing for a symmetric interest rate corridor around the main policy rate by making the standing borrowing rate higher than the standing deposit rate would complicate our analysis without altering the main results.

of the bank. In particular, if the bank is solvent, depositors receive $r_D$ on their entire deposit holdings at maturity. With probability $1 - q$, the bank defaults. In this case, depositors obtain a pro rata share of the remaining assets. The expected repayment to depositors must be equal to their outside option $u(r)$ such that

$$r_D = \frac{u(r) - \frac{(1-\hat{q})r\int_{-1}^{z}\max\{R+xD,0\}dF(x)}{D}}{\hat{q}}. \tag{12}$$

By substituting $r_D$ into Equation (3), we can solve for the bank's monitoring choice $\hat{q}(r_L, D; r)$. The partial effects of $r_L$, $r$, and $D$ on the banker's optimal monitoring $\hat{q}$ reflect the effects of these variables on her expected profits. As before, the effects of $r_L$ and $r$ are ambiguous, with the respective conditions now taking into account expected deposit flows.[17] However, the effect of $D$ on $\hat{q}$ is unambiguously negative, i.e., $\frac{\partial \hat{q}}{\partial D} < 0$. This is because $u(r) \geq r$ so deposits are relatively more expensive than borrowing from the central bank (cf. Assumption 1).

LEMMA 2. *The bank chooses a strictly positive loan issuance $L^*(r)$. Given Assumption 1, the bank minimizes its funding cost by choosing $R^* = -\sigma L^*$ and $D^* = (1-\sigma)L^*$.*

Lemma 2 shows that the bank borrows from the central bank on a permanent basis as long as this is feasible (i.e., if $\sigma > 0$). Even though the bank does not hold a positive level of reserves ex ante, the possibility that it ends up with a positive reserve balance due to random deposit inflows implies that the loan risk channel can still mitigate and even dominate the portfolio channel.

PROPOSITION 5. *The loan risk channel dominates the portfolio adjustment channel, i.e., $\frac{dr_L}{dr} < 0$, if and only if*

$$\frac{\partial \hat{q}(r_L^*, r)}{\partial r}\frac{r}{q(r_L^*, r)} > 1 + \frac{\hat{q}(r_L^*, r)F\left(\frac{\sigma}{1-\sigma}\right)}{1 - F\left(\frac{\sigma}{1-\sigma}\right)}. \tag{13}$$

[17] See the appendix for details.

As Proposition 5 shows, the condition for the loan risk channel to dominate the portfolio adjustment channel is similar to condition (11) when deposits are exogenous. The difference is that condition (13) depends on the probability that the bank ends up with safe asset holdings due to inflows into its depositors' accounts.

Inflows to deposits reflect the amount of safe assets that the bank cannot adjust optimally ex ante. Therefore, the probability of ending up with a positive balance can be interpreted as a measure of the ease with which the banker can adjust her safe assets. At one extreme, if the probability of an inflow of deposits becomes negligibly small, $F(\sigma/(1-\sigma)) \approx 1$, then condition (13) could never hold. In this case, the loan risk channel and the portfolio adjustment channel always go in the same direction and a reversal rate cannot exist. As is the case for a fully levered bank in Dell'Ariccia, Laeven, and Marquez (2014, Proposition 3), a lower risk-free rate leads to less risk-taking. On the contrary, if the bank would almost surely obtain a deposit inflow, i.e., $F(\sigma/(1-\sigma)) \to 0$, then condition (13) converges to our benchmark condition (11).

Condition (13) further allows us to illustrate the effect of permanent central bank lending programs on the existence of the reversal rate.

HYPOTHESIS 4. *The reversal rate becomes smaller if the central bank is willing to fund a larger share of the banker's lending, i.e.,* $\frac{\partial \hat{r}}{\partial \sigma} < 0$. *In the limit, for* $\sigma \to 1$*, the reversal rate ceases to exist.*

Consider the extreme case where the bank can finance its entire loan portfolio by borrowing from the central bank ex ante, i.e., $\lim \sigma \to 1$. In this case, a reversal rate would cease to exist.[18] This case is similar to the case with full deposit insurance, $\delta = 1$, in Section 4.1. The entire risk of the bank's loan issuance and the bank's exposure to interest rate risk would be borne by the central bank, and lower policy rates would unambiguously increase the bank's profit.[19]

[18] The right-hand side of Equation (13) converges to $\infty$, while the left-hand side assumes a finite value, implying that the condition could never be satisfied.

[19] We abstract from the possibility that the central bank can risk-adjust its interest rate when lending to the banker. In practice, central banks are able to

**Binding Liquidity Requirement.** Next, instead of Assumptions 2 and 3, we assume that the banker can endogenously choose her deposits, but she is required to hold a certain fraction of her deposits in the form of safe and liquid assets, e.g., reserves with the central bank or government bonds. This requirement is akin to the LCR that banks must satisfy under Basel III regulations (see Brunnermeier, Abadi, and Koby 2023 for a similar assumption). As we now show, under a binding liquidity requirement, the portfolio adjustment channel and the loan risk channel always move into the same direction. However, they both switch sign once the safe asset effect dominates the deposit pass-through effect. The banker's liquidity requirement can be written as

$$R \geq \rho D,$$

where $\rho$ is now the exogenously given regulatory liquidity ratio. To the extent that $u(r) \geq r$, the liquidity requirement is binding. Since the expected profits are strictly decreasing in $D$, the banker minimizes the amount of deposits. Combining the liquidity requirement and the funding constraint yields

$$\frac{L}{1-\rho} = D.$$

Substitution into the banker's profits yields

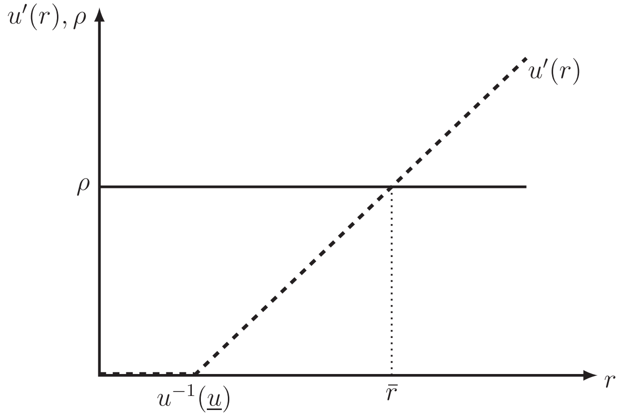
$$\Pi = q\left(r_L - \frac{r_D - \rho r}{1-\rho}\right) L(r_L) - \frac{\kappa q^2}{2}.$$

Because of the binding liquidity requirement, the direction of the portfolio adjustment channel also depends on the relationship between deposit pass-through and safe asset effect (like the loan risk channel). Thus, compared to Equation (9), the two channels are perfectly aligned, and we have

$$\frac{dr_L^*}{dr} = \underbrace{\frac{\partial r_L^*}{\partial r}}_{\substack{\text{portfolio adjustment}\\ \text{channel}}} + \underbrace{\frac{\partial r_L^*}{\partial q} \times \frac{\partial \hat{q}(r_L^*, r)}{\partial r}}_{\text{loan risk channel}} \propto \left(\frac{u'(r) - \rho}{1-\rho}\right). \tag{14}$$

achieve some degree of risk adjustment by lending against collateral and applying haircuts to riskier asset classes.

**Figure 6. Reversal Rate with a Binding Liquidity Requirement**




**Note:** For $r > \bar{r}$, the portfolio adjustment and the loan risk channel are positive, while they become negative for $r < \bar{r}$.

PROPOSITION 6. *Under a binding liquidity requirement, a reversal of monetary transmission occurs whenever the safe asset effect dominates the deposit pass-through effect. The reversal rate is*

$$\hat{r} = \bar{r}, \qquad \textit{where } \bar{r} \textit{ satisfies } u'(r) = \rho.$$

*A higher liquidity requirement weakens the transmission of monetary policy.*

Figure 6 illustrates the case of a binding liquidity requirement. Because $\rho$ is now exogenously determined, the solid curve is flat at the level set by regulation. For $r < \bar{r}$, the safe asset effect dominates and reverses both the loan risk and the portfolio adjustment channel, i.e., a further reduction in the risk-free rate leads to a higher loan rate and a reduced loan issuance.

The case of a binding liquidity requirement allows us to emphasize a potential cost associated with liquidity requirements. The literature usually discusses the direct costs of liquidity requirements, i.e., the opportunity cost of foregoing profitable investments when a larger share of deposits is held in the form of more liquid but less profitable assets. Our model reveals another indirect cost of liquidity requirements, namely the costs that arise from the impairment of the monetary transmission channel. As can be seen in Equation (14), an increase in $\rho$ reduces the effect of $r$ on $r_L^*$. Moreover, once $\rho$ is sufficiently high, monetary transmission is reverted.

### *4.3 Depositors' Outside Option*

Finally, let us briefly discuss how the results in our model depend on Assumption 1. The crucial element of Assumption 1 is the lower bound on the outside option, whereas the additional assumptions (convexity of $u(r)$ and continuity of $u'(r)$) are technical and imposed for the sake of tractability. Consider the following example where depositors, instead of holding deposits, could either invest into a risk-free bond that pays $r$ at date 1 or hold cash which provides a per-unit convenience yield $\theta$ and requires a per-unit storage cost $\zeta$. Thus, $u(r) = \max\{1 + \theta - \zeta, r\}$ and $u'(r) = 1 - \mathbb{1}_{[r<1+\theta-\zeta]}$. For this specification of $u(r)$, the convexity and continuity assumptions ($u''(r) > 0$ and $\lim_{r\downarrow 1+\theta-\zeta} = 0$) fail to hold. Because $\rho \in (0, 1)$, it follows that $\rho > u'(r)$ if and only if $r < 1 + \theta - \zeta$. Since $u'(r)$ jumps discontinuously at $1 + \theta - \zeta$, the critical $\overline{r}$ at which the safe asset effect dominates the deposit pass-through effect equals the lower bound of the outside option. Hence, the safe asset effect can dominate the deposit pass-through effect for small values of $r$ even without the continuity and convexity imposed by Assumption 1.[20]

What about the possibility that deposits themselves provide a convenience yield so that $u(r) < r$? Because the main results in the paper depend on the marginal costs and benefits of deposits versus reserve assets, allowing for a convenience yield on deposits such that $u(r) < r$ for $r > u^{-1}(\underline{u})$ would leave the results in Propositions 1–3 unaffected.[21]

[20]The continuity and convexity assumptions ensure that $\overline{r} \geq u^{-1}(\underline{u})$ and that at $r = \overline{r}$ there is no discontinuity so deposit pass-through and safe asset effect are balanced at the margin.

[21]Changing the ordering between the outside option and the risk-free rate would, however, change the implications derived in Hypothesis 1. In this case, an exogenous increase in deposits would increase the banker's expected profit and therefore increase her incentives to monitor and lead her to issue more loans. Note, however, that $u(r) < r$ would allow the bank to make a risk-free profit from

The key element in Assumption 1 is the assumption that the outside option of depositors cannot fall below $\underline{u}$. Suppose we dispense with this assumption and set $u(r) = r$ for all values of $r$, which is a standard assumption in the corporate finance and banking literature, e.g., Dell'Ariccia, Laeven, and Marquez (2014) and Martinez-Miera and Repullo (2017). Because $\rho \in (0, 1)$ while $u'(r) = 1$, the deposit pass-through effect dominates the safe asset effect for all values of $r$ and a lower interest rate always leads to an increase in monitoring, $\partial\hat{q}/\partial r < 0$. This mirrors the effect of $r$ on the bank's risk-taking incentives for the case of sufficiently high leverage in Dell'Ariccia, Laeven, and Marquez (2014, Proposition 3). As a consequence, the loan risk channel always amplifies the portfolio adjustment effect and lower interest rates unambiguously lead to a lower loan rate and higher loan issuance. This argument shows that the lower bound on the depositors' outside option is a key condition for the weakening of monetary transmission via the loan risk channel.

## 5. Conclusion

This paper argues that the empirically observed correlation between weaker monetary transmission and higher risk-taking in an environment of low interest rates (e.g., Miller and Wanengkirtyo 2020 or Arce et al. 2021) can be viewed as the consequence of an agency friction between banks and their depositors.

The main contributions of our paper are two. First, we show that lower policy rates lead banks to increase risk-taking when the pass-through to deposit rates is too small to compensate for the reduction in the profitability of banks' safe assets. Higher risk-taking, in turn, leads to a weakening of the monetary transmission because it induces banks to optimally raise loan rates and issue fewer loans.

Second, our model complements Brunnermeier, Abadi, and Koby (2023) by showing an alternative mechanism by which a reversal of monetary transmission can arise. The existence of a reversal

issuing deposits. To the extent that the bank could control the level of deposits (as in Section 4.2), the banker would issue as much deposits as possible.

rate depends on banks' characteristics (insured deposits, monitoring technology, leverage). Our model emphasizes that the reversal of monetary transmission is only an extreme manifestation of the more general phenomenon of weakened transmission due to higher risk-taking incentives in a low interest rate environment. This phenomenon should be of concern to central banks and may require them to devise policies that address the underlying causes of weaker transmission.

Our model suggests two policy implications that could help to alleviate the problem of weaker transmission. First, when operating in an environment with high excess reserves, central banks could implement reserve remuneration schemes that boost profits of banks holding excess reserves. While such schemes redistribute seigniorage revenues back to banks, they could nevertheless strengthen the transmission in an environment with protracted excess reserves and render monetary policy more effective. In this sense, our model provides a rationale for the two-tiered remuneration for excess reserves by the Eurosystem, which seeks to mitigate the effect of negative interest rates on bank profitability.[22]

Second, even though we abstracted from explicitly considering the effect of bank equity and capital regulation, our model can also speak to a recent debate on the importance of bank capitalization for monetary policy. In the context of our standard agency model, a capital requirement would weaken the link between loan rates and monitoring incentives. Put differently, an increase in loan risk would have a relatively smaller effect on the optimal loan rate if the bank must satisfy a larger capital requirement. As a consequence, a higher capital requirement would reduce the relative weight of the loan risk channel and strengthen monetary transmission via the portfolio adjustment channel. For banks with a smaller leverage, the reversal rate would be lower and the range of interest rates where transmission is unimpeded would be larger. Our model, therefore, echoes arguments by Gambacorta and Shin (2018) or Darracq Pariès, Kok, and Rottner (2020) who argue that bank capital matters not only for the central bank's financial stability but also for its monetary policy mandate and for the transmission of monetary policy.

[22] https://www.ecb.europa.eu/mopo/two-tier/html/index.en.html.

## Appendix

### A.1 Proofs

*Proof of Lemma 1.* Maximizing expected profits for a given deposit rate $r_D$ with respect to $q$ yields the first-order condition

$$r_L L - r_D D + rR - \kappa q = 0.$$

By substituting $r_D$ from the participation constraint, we can obtain $\hat{q}$ as the solution to the following implicitly defined function:

$$\phi(q, r_L, r) \equiv r_L L - \frac{u(r)D - rR}{q} - \kappa q = 0.$$

The latter is quadratic in $q$. Following Allen, Carletti, and Marquez (2015), we take the larger of the two roots, such that

$$\frac{\partial \phi}{\partial q} = \frac{u(r)D - rR}{q^2} - \kappa < 0.$$

Moreover, we have

$$\frac{\partial \phi}{\partial r} = \frac{R - u'(r)D}{q}$$

and, using the fact that $R = D - L(r_L)$,

$$\frac{\partial \phi}{\partial r_L} = r_L L'(r_L) + L(r_L) - \frac{r}{q} L'(r_L).$$

An application of the implicit function theorem yields the expressions for $\partial \hat{q}/\partial r_L$ and $\partial \hat{q}/\partial r$.

*Proof of Proposition 1.* From Equation (7), the first-order condition for the optimal loan rate is given by

$$\begin{aligned}\frac{d\Pi}{dr_L} &= \hat{q}(r_L, r)\left(r_L L'(r_L) + L(r_L)\right) - rL'(r_L)\\ &\quad + \frac{\partial \hat{q}}{\partial r_L} \underbrace{\left(r_L L(r_L) - \kappa \hat{q}\right)}_{=(u(r)D - rR)/q} = 0\end{aligned}$$

$$= \hat{q}(r_L, r)\left(r_L L'(r_L) + L(r_L) - \frac{r}{\hat{q}(r_L, r)} L'(r_L)\right) \times \left(1 - \frac{u(r)D - rR}{u(r)D - rR - \hat{q}^2\kappa}\right) = 0.$$

$\hat{q}$ and the second bracket are positive, so that the optimal $r_L^*$ satisfies condition (8) in the text.

The second-order condition, evaluated at the critical point $r_L^*$, becomes[23]

$$r_L L''(r_L^*) + 2L'(r_L^*) - \frac{r}{\hat{q}} L''(r_L^*) = -\frac{L''(r_L^*)L(r_L^*)}{L'(r_L^*)} + 2L'(r_L^*) < 0,$$

which is satisfied since $L(\cdot)$ is a decreasing and concave function. Thus, $r_L^*$ maximizes the bank's profits.

Applying the implicit function theorem to the first-order condition evaluated at $r_L^*$ yields

$$\frac{dr_L^*}{dr} = \frac{\partial r_L^*}{\partial r} + \frac{\partial r_L^*}{\partial q}\frac{d\hat{q}}{dr}$$
$$= -\frac{-\frac{L'(r_L^*)}{\hat{q}} + \frac{r}{\hat{q}^2}L'(r_L^*)\frac{\partial \hat{q}}{\partial r}}{-\frac{L''(r_L^*)L(r_L^*)}{L'(r_L^*)} + 2L'(r_L^*)} \gtreqless 0 \Leftrightarrow -\frac{L'(r_L^*)}{\hat{q}}\left(1 - \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}\right) \gtreqless 0, \tag{A.1}$$

where we replaced $\frac{d\hat{q}}{dr}$ with $\frac{\partial \hat{q}}{\partial r}$ because $\frac{\partial \hat{q}}{\partial r_L} = 0$ when evaluated at $r_L = r_L^*$.

Equation (A.1) implies that the loan risk channel weakens the portfolio channel whenever $\partial \hat{q}/\partial r > 0$, which is equivalent to $u'(r) < \rho$ (cf. Lemma 1).

Next, we show the existence of a value $\overline{r}$ such that for all $r < \overline{r}$, we must have $u'(r) < \rho$. Note that by Assumption 3, for all $r < u^{-1}(\underline{u})$ we have $\rho = R/D = 1 - L(r_L^*(r))/D > 0 = u'(r)$. If $r$ becomes sufficiently large, $R$ converges to a positive and finite value, while $u'(r)$ diverges (because of the strict convexity of $u(\cdot)$ for $r > u^{-1}(\underline{u})$) so that we have $u'(r) > \rho$ for sufficiently large $r$. Thus, there exists a smallest value $\overline{r}$ such that $u'(\overline{r}) = \rho$. For all $r < \overline{r}$, we have $u'(r) < \rho$.

[23]Note that the partial effect of $r_L$ on $\hat{q}$ is irrelevant for determining the sign of the second-order condition since $\partial \hat{q}/\partial r_L = 0$ when evaluated at $r_L^*$.

Thus, for $r < \overline{r}$, we have $u'(r) < \rho$ and, as a consequence of Lemma 1, $\partial\hat{q}/\partial r > 0$. From Equation (A.1) follows that the loan risk channel weakens the transmission via the portfolio channel for $r < \overline{r}$.

*Proof of Proposition 2.* The proof follows immediately from Equation (A.1):

$$\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; 1 < \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}}.$$

*Proof of Proposition 3.* We show the existence of $\hat{r}$ that satisfies

$$1 = \frac{\partial\hat{q}(r_L^*,\hat{r})}{\partial r}\frac{\hat{r}}{\hat{q}(r_L^*,\hat{r})}.$$

From the proof of Lemma 1 it follows that

$$\frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}} = \frac{(u'(r)D - R)r}{u(r)D - rR - \hat{q}^2\kappa} \geq 1 \;\Leftrightarrow\; (u(r) - u'(r)r)D \;\geq\; \kappa\hat{q}^2.$$

The last inequality requires that $u'(r)D \leq R$ since $u(r)D - rR < \kappa\hat{q}^2$ (cf. Lemma 1). Therefore, consider $u'(r) < \rho$. Since $u''(r) > 0$, the left-hand side of the above inequality is strictly decreasing in $r$. Since $u'(r) = 0$ for $r < u^{-1}(\underline{u})$, we have $\operatorname{argmax}_r\{u(r) - u'(r)r\} = u^{-1}(\underline{u})$. Thus, a necessary and sufficient condition for the existence of a reversal rate is that $\kappa$ satisfies $\kappa\hat{q}^2 \leq \underline{u}D$. Note further that

$$\frac{d\kappa\hat{q}(\kappa)^2}{d\kappa} = \frac{\hat{q}^2}{u(r)D - rR - \hat{q}^2\kappa}\left(u(r)D - rR + \kappa\hat{q}^2\right) \;<\; 0.$$

Thus, we can find a value $\underline{\kappa}$ such that $\underline{\kappa}\hat{q}(\underline{\kappa})^2 = \underline{u}D$ and where $\underline{\kappa}$ also satisfies the condition for $\partial\phi/\partial q < 0$ in the proof of Lemma 1. Since $(u(r) - u'(r)\hat{r})D - \kappa\hat{q}^2$ is strictly decreasing in $r$ for $r \leq \overline{r}$, there exists $\hat{r} < \overline{r}$ such that for $\kappa \geq \underline{\kappa}$

$$(u(\hat{r}) - u'(\hat{r})\hat{r})D - \kappa\hat{q}^2 = 0. \tag{A.2}$$

For $r < \hat{r}$, we have

$$(u(r) - u'(r)r)D > \kappa\hat{q}^2 \;\Leftrightarrow\; \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}} > 1.$$

*Proof of Hypothesis 1.* We consider an exogenous increase in the deposit volume and show that this leads to an increase in excess reserves, a higher reserves-deposit ratio, and less lending.

The equilibrium effect of an increased $D$ follows by applying the implicit function theorem to the two equilibrium conditions

$$r_L L(r_L) - \frac{u(r)D - r(D - L(r_L))}{q} - \kappa q = 0,$$
$$r_L L'(r_L) + L(r_L) - \frac{rL'(r_L)}{q} = 0.$$

Let $J^*$ denote the Jacobian of the above system of two equations evaluated at the optimum. From the proofs of Lemma 1 and Proposition 1 follows that $J^* < 0$ (when the variable vector is $(r_L, q)$). Note further that the second equation is independent of $D$. Thus, by the implicit function theorem

$$\frac{dq^*}{dD} \propto -\frac{u(r) - r}{q^*} < 0 \quad \text{and} \quad \frac{dr_L^*}{dD} \propto \frac{u(r) - r}{q^*} > 0.$$

Since $r_L$ increases in $D$, a higher $D$ leads to less lending and higher excess reserves

$$\frac{dL^*}{dD} = L'(r_L^*)\frac{dr_L^*}{dD} < 0 \quad \text{and} \quad dR = dD - L'(r_L^*)\frac{dr_L^*}{dD} > 0.$$

Finally, note that the latter implies also a higher reserves-deposit ratio $\rho$ because $\rho < 1$ and $L'(r_L^*)\frac{dr_L^*}{dD} < 0$ such that we obtain

$$\frac{d\rho}{dD} = \frac{1}{D}\left(1 - \rho - L'(r_L^*)\frac{dr_L^*}{dD}\right) > 0.$$

*Proof of Hypothesis 2.* Applying the implicit function theorem to Equation (A.2) yields

$$\frac{\partial \hat{r}}{\partial \kappa} = \frac{\frac{d\kappa \hat{q}^2}{d\kappa}}{-ru''(r)D - 2\kappa \hat{q}\frac{\partial \hat{q}}{\partial r}} > 0 \quad \text{and}$$

$$\frac{\partial \hat{r}}{\partial D} = \frac{-(u(r) - u'(r)r) + 2\hat{q}\kappa \frac{\partial \hat{q}}{\partial D}}{-ru''(r)D - 2\kappa \hat{q}\frac{\partial \hat{q}}{\partial r}} > 0.$$

*Proof of Proposition 4.* $\hat{q}$ is given by the solution to the following implicit function:

$$\phi(q, r_L, \delta, r) \equiv r_L L(r_L) - \left(\delta + \frac{1-\delta}{q}\right)(u(r)D - rR) - \kappa q = 0,$$

with

$$\frac{\partial \phi}{\partial q} = \frac{1-\delta}{q^2}(u(r)D - rR) - \kappa < 0,$$

$$\frac{\partial \phi}{\partial r} = \frac{(R - u'(r)D)(q\delta + (1-\delta))}{q^2} > 0 \Leftrightarrow \rho > u'(r),$$

$$\frac{\partial \phi}{\partial r_L} = r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta)}{q} r L'(r_L),$$

and

$$\frac{\partial \phi}{\partial \delta} = \frac{1-q}{q}(u(r)D - rR) > 0.$$

Given $\hat{q}$, the first-order condition for the banker's optimal loan rate is given by

$$\hat{q}\left(r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta}{q} r L'(r_L)\right)$$
$$\times \left(1 - \frac{(\hat{q}\delta + (1-\delta))(u(r)D - rR)}{(1-\delta)(u(r)D - rR) - \kappa \hat{q}^2}\right) = 0.$$

Since the second bracket is strictly positive, the optimal loan rate satisfies

$$r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta)}{q} r L'(r_L) = 0.$$

Application of the implicit function theorem yields

$$\frac{dr_L^*}{dr} \propto -(1-\delta)L'(r_L)\left(1 + \frac{\delta \hat{q}}{1-\delta} - \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}\right).$$

Thus, $\frac{dr_L^*}{dr} < 0$ if and only if $1 + \frac{\delta \hat{q}}{1-\delta} < \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}$.

*Proof of Hypothesis 3.* From the proof of Proposition 4 it follows that the reversal rate $\hat{r}(\delta)$ is given by the solution to

$$\frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}} - 1 - \frac{\delta \hat{q}}{1-\delta} = 0.$$

Using the expressions for $\partial \hat{q}/\partial r$, we can rewrite the latter as

$$u(r)D - \delta r R - (1-\delta)u'(r)rD - \kappa \hat{q}^2 = 0. \tag{A.3}$$

For $\delta = 0$, the above condition is equal to Equation (A.2), implying that $\hat{r}(\delta)$ converges to the value of the reversal rate in Proposition 3. Another application of the implicit function theorem to Equation (A.3), taking into account that for $r = \hat{r}$ we have $u'(r) < \rho$ and $\partial R/\partial r = 0$, implies $\frac{\partial \hat{r}}{\partial \delta} < 0$.

Note further that for $\delta \to 1$, Equation (A.3) cannot be satisfied since $\hat{q}$ is the larger root, which implies that $\kappa \hat{q}^2 - u(r)D + rR > 0$. Hence, for $\delta \to 1$, the reversal rate ceases to exist.

*Proof of Lemma 2 and Proposition 5.* The adjusted profit function becomes

$$\Pi = q\left(r_L L(r_L) + r\int_{-1}^{z}(R + x\,D)\,dF(x) - r_D D\right) - \frac{\kappa q^2}{2}.$$

Because $E[x] = 0$, we can simplify to the same profit function as in our baseline model,

$$\Pi = q\left(r_L L(r_L) + r\,R - r_D D\right) - \frac{\kappa q^2}{2}.$$

Inserting the participation constraint into the first-order condition for $q$ implicitly defines the function $\hat{q}(r_L, D, r)$

$$\begin{aligned}\phi(r_L, D, r) &= r_L L(r_L) + r\,R \\ &\qquad - \frac{u(r)D - (1-q)r\int_{-1}^{-\rho}(R + xD)\,dF(x)}{q} - \kappa q = 0.\end{aligned}$$

Taking the larger of the two roots, we obtain

$$\begin{aligned}\frac{\partial \phi}{\partial r} &= qR - u^{'} D + (1-q) \int_{-\rho}^{z} (R + xD) \, dF(x) \\ &= R - (1-q) \int_{-1}^{-\rho} (R + xD) \, dF(x) - u^{'} D\end{aligned}$$

and

$$\begin{aligned}\frac{\partial \phi}{\partial r_L} &= q((r_L - r)L^{'} + L) - (1-q) r L^{'} \int_{-\rho}^{z} \, dF(x) \\ &= q(r_L L^{'} + L) - r L^{'} + (1-q) r L^{'} \int_{-1}^{-\rho} \, dF(x),\end{aligned}$$

as well as

$$\begin{aligned}\frac{\partial \phi}{\partial D} &= qr - u(r) + (1-q) r \int_{-\rho}^{z} (1 + x) \, dF(x) \\ &= r - u(r) - (1-q) r \int_{-1}^{-\rho} (1 + x) \, dF(x) < 0,\end{aligned}$$

which is unambiguously negative for $r \leq u(r)$.

The first-stage profit function, given the required return for the expected equilibrium monitoring choice, becomes

$$\begin{aligned}\Pi(r_L, D; r) = \hat{q}(r_L L(r_L) + r\, R) - u(r) D \\ - (1-q) r \int_{-1}^{-\rho} (R + xD) \, dF(x) - \kappa \frac{\hat{q}^2}{2}.\end{aligned}$$

Differentiating with respect to $D$ and $r_L$ yields the first-order conditions for a profit maximum. As the bank optimally minimizes deposit costs, we evaluate the first-order condition at $D^* = (1-\sigma)L^*(r_L)$ and $R^* = -\sigma L^*(r_L)$, such that $\rho = -\frac{\sigma}{1-\sigma}$.

Using the implicit function theorem we obtain

$$\frac{dr_L}{dr} = -\frac{\begin{array}{c}-L' + (1-\hat{q})L' \int_{-1}^{\frac{\sigma}{1-\sigma}} \, dF(x)) \\ + \left(r_L L' + L - rL' \int_{-1}^{\frac{\sigma}{1-\sigma}} \, dF(x)\right) \frac{\partial \hat{q}}{\partial r}\end{array}}{\frac{\partial^2 \Pi}{\partial r_L^2}}.$$

For $r_L^*$ to be the optimal loan rate in equilibrium, we must have $\frac{\partial^2\Pi}{\partial r_L^2} < 0$. Therefore, $\frac{dr_L}{dr} < 0$ if and only if the numerator is negative. Using the first-order condition $\frac{\partial \Pi}{\partial r_L} = 0$, we can simplify to

$$\frac{r}{\hat{q}}\left(1 - \int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)\right)\frac{\partial \hat{q}}{\partial r} > 1 - (1-\hat{q})\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x) \Leftrightarrow \frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r}$$

$$> \frac{1 - (1-\hat{q})\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)}{\left(1 - \int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)\right)},$$

which corresponds to the condition in Proposition 5. Note that as $\sigma \to 1$, the left-hand side approaches zero and the right-hand side $\hat{q}$ such that the condition can never be fulfilled. If the bank can fund all loans by borrowing from the central bank, reversal rate cannot exist.

*Proof of Hypothesis 4.* The reversal rate $\hat{r}$ is implicitly defined by

$$\psi(\hat{r},\sigma) \equiv \frac{\hat{r}}{\hat{q}}\frac{\partial \hat{q}}{\partial r} - 1 - \hat{q}\left(\frac{F(\frac{\sigma}{1-\sigma})}{1 - F(\frac{\sigma}{1-\sigma})}\right) = 0.$$

By the implicit function theorem, $\frac{\partial \hat{r}}{\partial \sigma} = \frac{\partial \psi/\partial \sigma}{\partial \psi/\partial r} < 0$, because $\frac{F(\frac{\sigma}{1-\sigma})}{1-F(\frac{\sigma}{1-\sigma})}$ strictly increases in $\sigma$ as the distribution function $F(\cdot)$, is an increasing function and at $r = \hat{r}$, we have $\partial\psi/\partial r < 0$.

*Proof of Proposition 6.* The banker's optimal monitoring choice is the same as in the benchmark model, i.e., $\hat{q}$ is given by the implicitly defined function $\hat{q}(r_L, r)$. Substituting $\hat{q}$ and the deposit rate into the expected profits yields

$$\Pi = \hat{q} r_L L(r_L) - \left(\frac{u(r) - \rho r}{1-\rho}\right) L(r_L) - \frac{\kappa \hat{q}^2}{2}.$$

The first-order condition determining the bank's loan issuance is given by

$$\left(\hat{q} r_L - \frac{(u(r) - \rho r)}{1-\rho}\right) L'(r_L) + \hat{q} L(r_L) + \frac{(u(r) - \rho r) L(r_L)}{\hat{q}} \frac{\partial \hat{q}}{\partial r_L} = 0.$$

Using the expression for $\partial \hat{q}/\partial r_L$ implies that the optimal loan rate $r_L^*$ must satisfy

$$\left(r_L^* - \frac{(u(r) - \rho r)}{\hat{q}(1-\rho)}\right) L'(r_L^*) + L(r_L^*) = 0.$$

The second-order sufficient condition is satisfied when evaluated at $r_L^*$. Totally differentiating the first-order condition yields

$$\frac{dr_L^*}{dr} = \frac{\frac{L'(r_L)}{\hat{q}}\left(1 + \frac{(u(r)-\rho r)L(r_L)}{\hat{q}\left(\kappa - \frac{(u(r)-\rho r)L(r_L)}{\hat{q}^2}\right)}\right)}{\frac{\partial^2 \Pi}{\partial r_L^*}} \cdot \left(\frac{u'(r) - \rho}{1-\rho}\right).$$

Since the term multiplying $(u'(r) - \rho)/(1-\rho)$ is strictly positive, it follows immediately that

$$\frac{dr_L^*}{dr} \gtrless 0 \Leftrightarrow u'(r) \gtrless \rho \Leftrightarrow r \gtrless \bar{r},$$

where $\bar{r}$ solves $u(r) = \rho$.

### *A.2 Proportional Monitoring Cost*

This section shows that the key result in Proposition 2, i.e., that

$$\frac{dr_L}{dr} < 0 \Leftrightarrow \frac{\partial \hat{q}(r_L^*, r)}{\partial r} \frac{r}{\hat{q}(r_L^*, r)} > 1$$

remains unchanged if monitoring costs are proportional to loan issuance, i.e.,

$$c(q, r_L) = \frac{\kappa}{2} q^2 L(r_L).$$

To show this, we derive the first-order condition determining the bank's optimal monitoring effort:

$$r_L L(r_L) - r_D D + r(D - L(r_L)) - cqL(r_L) = 0.$$

The optimal monitoring effort $q(r, r_L)$ is implicitly defined by the first-order condition after substituting for $r_D$:

$$r_L L(r_L) - cqL(r_L) - \frac{u(r)D - r(D - L(r_L))}{q} = 0.$$

Application of the implicit function theorem yields

$$\frac{\partial \hat{q}(r_L, r)}{\partial r_L} = \frac{r_L L'(r_L) + L(r_L) - \frac{r}{q} L'(r_L) - cqL'(r_L)}{cL(r_L) - \frac{u(r)D - rR}{q^2}} \gtrless 0,$$

and

$$\frac{\partial \hat{q}(r_L, r)}{\partial r} = \frac{R - u'(r)D}{cL(r_L) - \frac{u(r)D - rR}{q^2}} \gtrless 0.$$

Given $\hat{q}(r_L, r)$, the bank maximizes its profits by choosing the loan rate $r_L$. The profit function is given by

$$\hat{q}(r_L, r) r_L L(r_L) + r(D - L(r_L)) - u(r)D - \frac{c}{2} \hat{q}(r_L, r)^2 L(r_L).$$

Differentiating with respect to $r_L$ yields the first-order condition that pins down $r_L^*$:

$$q(r_L, r) \left( r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - \frac{c}{2} q(r_L, r) L'(r_L) \right)$$
$$+ (r_L L(r_L) - cq(r_L, r) L(r_L)) \frac{\partial q(r_L, r)}{\partial r_L} = 0.$$

Dividing the latter equation by $\hat{q}$ and adding and subtracting $c\hat{q}L'/2$, we obtain

$$\left( r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - cq(r_L, r) L'(r_L) \right)$$
$$+ (r_L L(r_L) - cq(r_L, r) L(r_L)) \frac{\partial q(r_L, r)}{\partial r_L} \frac{1}{\hat{q} r_L, r)} + \frac{c}{2} q(r_L, r) L'(r_L) = 0.$$

Using the first-order condition for monitoring to replace $r_L L(r_L) - c\hat{q}$, we obtain

$$\left( r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - cq(r_L, r) L'(r_L) \right)$$
$$+ \frac{u(r)D - r(D - L(r_L))}{q(r_L, r)^2} \frac{\partial \hat{q}(r_L, r)}{\partial r_L} + \frac{c}{2} q(r_L, r) L'(r_L) = 0.$$

Substituting the expression for $\partial \hat{q}/\partial r_L$ and collecting terms, we finally obtain

$$cL(r_L)\left(r_L L'(r_L) + L(r_L) - \frac{r}{q}L'(r_L) - cq(r_l, r)L'(r_L)\right) + \frac{c}{2}q(r_L, r)L'(r_L)\left(cL(r_L) - \frac{u(r)D - r(D - L(r_L))}{q(r_L, r)^2}\right) = 0.$$

The second-order condition is strictly negative when evaluated at the critical point $r_L^*$ that satisfies the latter equation. Thus, from the implicit function theorem follows that the sign of $dr_L^*/dr$ is equal to the sign of the derivative of the first-order condition with respect to $r$, i.e., we have (for simplicity, we have dropped the arguments from functions $\hat{q}$ and $L$):

$$\begin{aligned}
\frac{dr_L^*}{dr} &\propto -\frac{cLL'}{\hat{q}} - \frac{cL'}{2}\frac{u'(r)D - (D - L)}{\hat{q}} \\
&\quad + \left(\frac{cLL'r}{\hat{q}^2} - \frac{c^2LL'}{2} + \frac{cL'}{2}\frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial \hat{q}}{\partial r} \\
&= -\frac{cLL'}{\hat{q}} - \frac{cL'}{2}\left(cL - \frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial \hat{q}}{\partial r} \\
&\quad + \left(\frac{cLL'r}{\hat{q}^2} - \frac{c^2LL'}{2} + \frac{cL'}{2}\frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial \hat{q}}{\partial r} \\
&= -\frac{c}{\hat{q}}LL'\left(1 - \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}\right),
\end{aligned}$$

where the second line follows from using the expression for $\frac{\partial \hat{q}}{\partial r}$ from above. Since $-cL(r_L)L'(r_L)/\hat{q}(r_L, r) > 0$, it follows that

$$\frac{dr_L^*}{dr} < 0 \Leftrightarrow \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}} > 1,$$

which is the same condition as in Proposition 2 where monitoring costs are independent of $L(r_L)$.

Note, while the condition for the marginal effect of $r$ on $r_L^*$ remains unchanged, a comparison of the respective first-order conditions shows that if the monitoring costs are proportional to loan issuance, the bank issues fewer loans (sets a higher loan rate) to reduce the monitoring costs.

### *A.3 Different Outside Options for Insured Depositors*

In the main text, we assume that uninsured and insured depositors have the same outside option $u(r)$. Here, we show that Proposition 4 and Hypothesis 3 remain unchanged even if insured depositors have a different outside option. To this end, let $u_I I(r)$ denote the outside option of insured depositors. The outside option of the uninsured depositors remains denoted by $u(r)$.

The first-order condition for the banker's monitoring choice is given by

$$r_L(L(r_L) + rR - (\delta u^I(r) + (1-\delta)r_D)D - \kappa q = 0,$$

where $r_D$ denotes the interest rate on uninsured debt. Substituting Equation (5) for $r_D$ into the first-order condition yields the implicit function for $\hat{q}(r_L, r)$:

$$\begin{aligned}\phi(\hat{q}, r_L, r) \equiv\ & r_L(L(r_L)) \\ & - \frac{(\delta\hat{q}u_I I(r) + (1-\delta)u(r))D - (\hat{q} + (1-\delta)(1-\hat{q}))rR}{\hat{q}} \\ & - \kappa\hat{q} = 0.\end{aligned}$$

Again, choosing the larger root for $\hat{q}$, we have $\frac{\partial\phi}{\partial\hat{q}} \equiv \phi_{\hat{q}} < 0$ and

$$\frac{\partial\phi}{\partial r_L} \equiv \phi_{r_L} = r_L L'(r_L + L(r_L) - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'(r_L).$$

Given the implicitly defined function $\hat{q}(r_L, r)$, we next turn to the banker's optimal choice of $r_L$. Substituting the uninsured deposit rate and $\hat{q}$ into the profit function, we obtain

$$\begin{aligned}\pi(r_L) = & \hat{q}r_L L(r_L) + (\hat{q} + (1-\hat{q})(1-\delta))rR \\ & - (\delta u_I(r) + (1-\delta)u(r))D - \frac{\kappa}{2}\hat{q}^2.\end{aligned}$$

The first-order condition for $r_L$ is given by

$$\begin{aligned}\pi'(r_L) = & \hat{q}\left(r_L L' + L - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'\right) \\ & + (r_L L + \delta(rR - u_I(r)D) - \kappa q)\frac{\partial\hat{q}}{\partial r_L} = 0.\end{aligned}$$

Substituting from the first-order condition for effort choice,

$$r_L L - \kappa\hat{q} = \frac{(\delta\hat{q}u_I(r) + (1-\delta)u(r))D - (\hat{q} + (1-\delta)(1-\hat{q}))rR}{\hat{q}},$$

and the expression for $\partial\hat{q}/\partial r_L$, it follows that the optimal loan rate $r_L^*$ must solve

$$r_L L'(r_L) + L(r_L) - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'(r_L) = 0.$$

As the second-order condition for a profit maximum must be negative, it follows from the implicit function theorem that

$$\begin{aligned}\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; & -\frac{(\hat{q} + (1-\delta)(1-\hat{q}))}{\hat{q}}L'(r_L) \\ & + \left(-\frac{r}{\hat{q}}L'(r_L) + \frac{(\hat{q} + (1-\delta)(1-\hat{q}))r}{\hat{q}^2}L'(r_L)\right)\frac{\partial\hat{q}}{\partial r} < 0.\end{aligned}$$

Rewriting the latter equation yields

$$\begin{aligned}\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; & -\frac{(1-\delta)}{\hat{q}}L'(r_L)\left(\frac{r}{\hat{q}}\frac{\partial\hat{q}}{\partial r} - \left(1 + \frac{\hat{q}\delta}{1-\delta}\right)\right) \\ < 0 \;\Leftrightarrow\; & \frac{r}{\hat{q}}\frac{\partial\hat{q}}{\partial r} > 1 + \frac{\delta\hat{q}}{1-\delta},\end{aligned}$$

which is the same condition as in Proposition 4.

However, note that while the above condition is the same as in the main text, the magnitude of the thresholds $\bar{r}$ and $\hat{r}$ changes compared to the model with identical outside options. To see this, consider the sign of

$$\frac{\partial\hat{q}}{\partial r} > 0 \;\Leftrightarrow\; \rho > \frac{\left(\delta\hat{q}\frac{u_I'(r)}{u'(r)} + (1-\delta)\right)u'(r)}{\delta\hat{q} + (1-\delta)}.$$

It follows that the relative deposit pass-through, i.e., $u_I'(r)/u'(r)$, determines whether or not the threshold rates $\bar{r}$ and $\hat{r}$ change compared to the baseline model. Whenever the interest rate pass-through to insured and uninsured depositors is the same, $u_I'(r) = u'(r)$, then $\bar{r}$ and $\hat{r}$ remain unchanged. Otherwise, if, say, $u_I'(r) < u(r)$, then the threshold $\bar{r}$ becomes larger, i.e., the range of risk-free rates where the bank's risk-taking incentives increase following a marginal increase in $r$.

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# Switching from Cash to Cashless Payments during the COVID-19 Pandemic and Beyond*

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Using a survey of 5,504 respondents from 22 European countries, we examine preferences regarding cash and cashless payments at the point of sale (POS) during the COVID-19 crisis. Consumers favor cashless transactions when they believe that handling cash presents a higher risk of infection. Moreover, the habits they develop during periods of restrictions and lockdowns appear to further diminish their appetite for transacting in cash. Not only do these factors affect current choice of payment method, but they also influence declared future intentions to move away from cash after the pandemic is over.

JEL Codes: E41, E42, I12, I18.

## 1. Introduction

The highly contagious coronavirus disease 2019 (COVID-19) was declared a pandemic on March 11 (World Health Organization 2020).

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Up to the end of December 2023, it infected officially more than 774 million people and claimed almost 7 million lives (Mathieu et al. 2020). The mental, social, and economic lives of virtually everyone around the globe were affected by this health risk, profoundly changing people's habits and behaviors. In an attempt to limit the spread of the virus, governments enforced rules pertaining to social distancing and the use of face masks, advocated self-isolation, handwashing, and other types of hygienic measures. Partially due to government-imposed lockdowns, a significant reduction in people's mobility and consumption was observed, with a substitution from in-store to online shopping becoming particularly prominent (Bounie, Camara, and Galbraith 2023).

At the same time, an unprecedented outpouring of speculation about the possible link between handling physical money and COVID-19 infections has emerged (Auer, Cornelli, and Frost 2020). Research regarding this phenomenon indicated that a significant fraction of the population reduced their transactional use of cash in response to the pandemic. In its IMPACT study, the European Central Bank (2020) showed that about 40 percent of respondents in the euro area curtailed their use of cash and 38 percent of them declared that the main stimulus for their changed payment behavior was the possibility of being infected through touching banknotes. Surveys conducted by the Federal Reserve System (Kim, Kumar, and O'Brien 2020), Bank of Canada (Chen et al. 2020), and National Bank of Poland (Kotkowski, Dulinicz, and Maciejewski 2022) reached similar conclusions, noting further that some risk-averse merchants ceased to accept cash as a means of payment. Using the Dutch payment diary data, Jonker et al. (2022) shed more light on demographic and transaction-specific drivers that influence the change in payment habits due to COVID-19. Notably, the effect of the pandemic on the transactional utility of cash is manifest not only in declarations of individual respondents but also in more aggregate statistics. The studies focusing on data from retail systems, national payment schemes, or particular banks in Canada, Switzerland, Italy, and France revealed a rapid increase in the adoption of cashless payments, despite a decline in the level of general consumption (see Ardizzi, Nobili, and Rocco 2020; Bounie, Camara, and Galbraith 2023; Dahlhaus and Welte 2021; Kraenzlin, Meyer, and Nellen 2020).

In this paper, we further probe the utility of cash during the COVID-19 crisis. Using a unique data set, we can model respondents' inclination to switch from cash to cashless instruments. The richness of our data source permits us to disentangle two critical pandemic-related factors that drive underlying behaviors. Firstly, there is the direct impact of an individual's perception of viral transmission risk associated with touching banknotes and coins. Secondly, and equally importantly, this global health emergency has changed habits related to shopping, human interaction, mobility, health regimens, and ways of working. Entrenchment of these habits could have an indirect but lasting influence on payment method preferences. Our factor analysis indicated that those shifts in behavioral patterns could be categorized by whether they occurred in the physical sphere or in the cyberspace. By controlling for a wide range of respondents' and country-level characteristics, we extricated these direct and indirect influences in a logistic regression setting. We document that both fear of contagion and altered habits played a prominent role in the decision to abandon cash for transactional purposes during the COVID pandemic. Analogous results are obtained when modeling the respondents' intention to use cashless instruments more frequently after the pandemic is over. Notably, changes in habits related to physical contact exerted a more statistically and economically powerful impact on payment preferences of respondents than the altered behaviors in the online environment.

Several aspects distinguish our work from existing studies. The analysis of cash usage by the European Central Bank (2020) performed during the pandemic period reports only aggregated figures, without attempting to link COVID-19 responses to the selection of payment method at an individual level. Although Jonker et al. (2022) overcame this shortcoming by explicating changes in the payment behavior of Dutch consumers, our analysis is on a much larger scale—we examine 22 European countries rather than 1. What is more, to the best of our knowledge, this is the first study empirically linking the magnitude of fear of viral contagion with the choice of payment instrument. Similarly, the fact that changes in other habits could have a domino-like effect on peoples' payment choices has hitherto not been considered in the literature. To add further depth to our inquiry, we not only consider historical preferences towards cashless payments, but also interrogate individuals' declarations about their future payment intentions after the COVID-19 pandemic is over. Our empirical model controls for a wide range of factors, including perceptions of different payment instruments, experience of using them, stances on privacy, general technical literacy, a variety of sociodemographic factors, and country-level variables such as the number of COVID-related deaths and size of the shadow economy.

The remainder of the paper is organized as follows. Section 2 presents a literature review, which embodies two important themes. It starts by reviewing the evidence on SARS-CoV-2 survival on banknotes and coins, moving subsequently to a consideration of consumer payment behavior. Section 3 outlines our methodological approach, while Section 4 provides a description of the data set, definitions of variables, and a set of summary statistics. Our main empirical results and their interpretation are included in Section 5, and this is followed by a battery of robustness checks in Section 6. Section 7 presents reflections on the practical implications of our findings. The paper ends with concluding remarks.

## 2. Literature Review

### *2.1 Methods of Payments and Infectious Disease Transmission*

Studies examining the spread of pathogens through the use of cash date back to the 1970s (see, for instance, Abrams 1972). In absence of disinfection, various types of microbes could adhere to the surface of currency, leading to the transmission of communicable diseases. A study by Vriesekoop et al. (2016) exploring bacterial survival concluded that microbial persistence is greater on paper banknotes than on polymer bills and coins. According to the estimates of Pope et al. (2002), about 94 percent of \$1 bills are contaminated with pathogenic or potentially pathogenic bacteria. This statistic reaches 100 percent for currency notes in Ghana (Tagoe et al. 2009). Bills could also potentially harbor fungi and yeast (Basavarajappa, Rao, and Suresh 2005), parasites (Uneke and Ogbu 2007), and viruses (Maritz et al. 2017). The literature review conducted by Angelakis et al. (2014) concludes that banknotes retrieved from hospitals may carry antibiotic-resistant MRSA, while those from food outlets may be tainted with salmonella and E. coli.

While the existence of the monetary microbiome is well documented in the medical literature, one may wonder to what extent this message reverberated through broader society prior to the COVID-19 crisis. The reaction to the study of Gedik, Voss, and Voss (2013) epitomizes the attitudes of the bygone era. Their insightful analysis examined bacterial survival on banknotes from different countries. For their work, the authors received a satirical Ig Nobel Prize for economics in 2019. One year later, the escalating death toll from coronavirus caused a sea change in general attitudes towards this problem.

Discovery of durability of SARS-CoV-2 on surfaces (Chin et al. 2020; van Doremalen et al. 2020) posed a question as to whether the virus could be transmitted via cash. Having put a droplet of the virus on a banknote, Chin et al. (2020) observed that the note remained infectious for a period of four days. Harbourt et al. (2020) investigated the persistence of SARS-CoV-2 on U.S. banknotes produced from a blend of linen and cotton. At a temperature of 4°C, the virus was detectable for 96 hours on \$1 bills and for 72 hours on \$20 notes. Surface stability however reduced with ambient temperature, with the virus being viable for eight hours at 22°C and for four hours at 37°C. A study commissioned by the Bank of England (Caswell et al. 2020) found that the virus maintained its stability on banknotes for one hour, with its presence being dramatically reduced to about 5 percent of its initial level over the subsequent five hours. Those are very low estimates compared to those of Riddell et al. (2020), who claim that the coronavirus causing COVID-19 is still detectable on polymer and paper notes 28 days following inoculation. With regard to coins, the time to complete virus decay may depend on the metal used to mint the coin. For instance, this duration appears to be 8 hours for copper and 48 hours for stainless steel (van Doremalen et al. 2020). At the time of writing, there are still many questions as to whether cash is indeed a fomite and what exactly is the severity of the risks involved. The general public was bombarded with mixed messages in this regard. For instance, the World Health Organization has recommended that people wash their hands after coming in contact with notes and coins (Pal and Bhadada 2020). However, a recent study commissioned by the European Central Bank (ECB) showed that the risk of contracting the disease from contact with cash is very low and that cash is reasonably safe to use (Tamele et al. 2021).

The question arises as to whether the dangers posed by cash can be circumvented by switching to cashless payments. After all, SARS-CoV-2 can remain stable on plastic surfaces for seven days (Chin et al. 2020), which in itself could endanger users of payment card terminals and PIN (personal identification number) pads. However, limits on contactless payments were increased in many countries during the pandemic (Mastercard 2020), obviating the need to input a PIN code for most transactions at the point of sale. The vast majority of transactions conducted online or via mobile banking also do not require contact with potentially contaminated surfaces. Consequently, one may argue that changing one's payment habits may reduce the risk of infection.

The stance of money issuers vis-à-vis the problem of jeopardized public health proved to be somewhat confusing. Central banks differed markedly in terms of their response to information about the potential threat posed by cash. Some central banks (such as the ECB and those of the United Kingdom, Germany, Austria, Sweden, and South Africa) either stressed that the risk of SARS-CoV-2 transmission through cash is minimal compared to other frequently touched objects or refused to acknowledge the possibility of contagion altogether. But a few other nations took different approaches. For instance, central banks in the United States, China, South Korea, Kuwait, Hungary, and Poland started to quarantine and disinfect cash (Auer, Cornelli, and Frost 2020; King and Shen 2020). A regional branch of the People's Bank of China proceeded to destroy banknotes that had circulated in hospitals, wet markets, and on buses (Yeung 2020). The central banks of Georgia and India started to promote cashless payments, while, at the other end of the spectrum, monetary authorities in Canada, Portugal, and Poland appealed to retailers who stopped accepting cash to discontinue such practices. Their pleas were motivated by concerns over those who are financially excluded.

### *2.2 Consumer Payment Behavior*

Consumer payment behavior has been a burgeoning field of research since the 1980s, starting with the seminal work of Boeschoten and Fase (1989). Nowadays, country-specific inquiries into this topic are primarily carried out by central banks. The U.S. Federal Reserve has been conducting an annual Survey of Consumer Payment Choice since 2008 (Foster, Greene, and Stavins 2020) and a Diary of Consumer Payment Choice since 2015 (Greene and Stavins 2020). In a similar vein, studies regarding Dutch payment behavior have been undertaken by De Nederlandsche Bank (DNB) since 2010 (see DNB 2020). A number of other countries, including Australia, Canada, Denmark, Sweden, Germany, Poland, and Norway, also endeavor to run similar surveys at regular intervals. Going beyond national level, the ECB performed its pan-euro-area study in 2016 (see Esselink and Hernández 2017) and 2019 (ECB 2020). Taken together, the evidence gathered reveals a pattern of steady decline in the share of retail transactions conducted using cash. In the United States this share fell from about 30 percent in 2009 to 21.5 percent in 2019 (Foster, Greene, and Stavins 2020). This downward-sloping trend is mirrored in the United Kingdom with a decline from about 80 percent in 1990 to 23 percent in 2019 (Caswell et al. 2020) and in the euro area, where the proportion of cash POS and P2P (peer-to-peer) payments decreased from 79 percent to 73 percent between 2016 and 2019 (ECB 2020).

Personal payment choice is an outcome of myriad variables, both intrinsic and extrinsic to a given individual. Internal aspects embrace perceptions of different payment instrument characteristics such as perceived speed of payment, security, ease of use, and budget control (Koulayev et al. 2016; Schuh and Stavins 2016), or stances on issues like privacy and trust (Png and Tan 2020). External influences could incorporate, for instance, socioeconomic and sociopsychological factors (Stavins 2001; van der Cruijsen and van der Horst 2019). It is worth noting that the characteristics of transactions could be also important in terms of influencing the outcome. Such characteristics encompass the transaction amount (Arango-Arango et al. 2018; Wang 2016), the possibility of paying in the way one desires (Bagnall et al. 2016; Bounie, François, and Van Hove 2017), steering mechanisms used by merchants (Arango, Hyunh, and Sabetti 2015; Stavins and Shy 2015), rewards offered by issuers of cashless payments (Bolt, Jonker, and van Renselaar 2010; Simon, Smith, and West 2010), or costs associated with the transaction (Arango-Arango et al. 2018).

Prior to the COVID-19 outbreak, there was little research investigating the link between spread of contagious disease and change in people's payment behavior. Closest to this subject is the work by Galbraith and Tkacz (2013), who used payment systems data to examine the economic impact of extreme events, like the 9/11 terrorist attacks and the SARS epidemic of March–June 2003. However, at the time, the SARS epidemic did not alter behavior significantly enough to generate detectable effects. Following the escalation of COVID-19, more research on this topic started to emerge. Apart from our study, other papers that used individual-level data include the aforementioned work of Jonker et al. (2022) and that of Saroy et al. (2022) who documented a pandemic-induced shift towards cashless payments in India. The authors argued that awareness of digital payment methods, access to different instruments, and relief welfare transfers affected the shift. Another study by Cevik (2020) reported that the spread of contagious diseases like Ebola, SARS, malaria, or yellow fever decreased the demand for physical money in the affected areas and noted that this observation may have ramifications for the current situation.

Ours is a paper that focuses specifically on how the context of the COVID-19 pandemic affected intentions to use cash. In our exploration, we distinguish two important mechanisms through which such intentions could be affected. First, individuals may exhibit varying degrees of subjective fear attributable to dealing with currency that could potentially be virally contaminated. Such fears would be a direct stimulus steering consumers towards cashless transactions, insofar as cashless transactions are perceived as a lower contagion risk. Second, there could be an indirect effect arising from the fact that the pandemic has profoundly altered our ways of life. Bound by government restrictions and by the commonsensical avoidance of jeopardy, individuals showed a stronger preference for online shopping (Bounie, Camara, and Galbraith 2023; Watanabe and Omori 2020), reduced their mobility and consumption (Bounie, Camara, and Galbraith 2023; Carvalho et al. 2021; Mínguez, Urtasun, and de Mirasierra 2020), modified their working practices (Bick, Blandin, and Mertens 2023; Brynjolfsson et al. 2020), and moved their social interactions into cyberspace (Nabity-Grover, Cheung, and Thatcher 2020). Such lifestyle transformations could have serious ramifications for personal preferences over payment methods.

A question arises as to whether these lifestyle changes have become habitual and therefore enduring. We need to bear in mind that focal attention and consciousness of choice feature prominently when an action is performed for the first time. The more an activity is repeated in a stable context, the more automatic the cognitive processes become, thereby permitting speedy action (Carden and Wood 2018; Shiffrin and Schneider 1977). Lally et al. (2010) examined changes in daily routines in order to gauge how long it would take an individual to develop a new habit. In their research, the participants' median time to reach a "plateau of automaticity" was 66 days. The duration of the pandemic has exceeded this estimate by a substantial margin, allowing sufficient time for habit formation. Arguably, the context could be also viewed as stable in the sense that the possibility of infection was ubiquitous and ever-present. However, there is a fair amount of uncertainty as to how people would behave if the context were to change. For instance, the epidemic could be eradicated through a program of mass vaccination. In response to this, some individuals may remain entrenched in the habits they acquired, while others may devote more attention to accommodating the altered landscape in their decisionmaking. Any persistence of COVID-induced habits could affect general attitudes towards using cash in the long run. Our questionnaire deliberately asks respondents which of their behavioral changes are likely to endure one year after the end of the COVID-19 pandemic.

## 3. Methodology

Two dependent dummy variables are considered in our modeling. They record whether respondents started to use more cashless payments due to the COVID-19 pandemic (*Cashless Switch*) and whether they declare an intention to use cashless payments more often after the pandemic is over (*Cashless Intention*). Since our data set is cross-sectional rather than longitudinal in nature, we are unable to verify whether the declared intentions materialize as an actual behavior in the future. However, extant empirical evidence indicates that, when it comes to adopting technologies, there is a high correlation between intentions and actual subsequent usage (see, for instance, Davis 1989). Perhaps more importantly, the behavioral intention is considered an antecedent and a stimulus for technology adoption in the most prominent theoretical models, such as the theory of reasoned action (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975) or the technology acceptance model (Davis 1989).

Since our dependent variables measuring whether a respondent switched or intends to switch to cashless payments are binary in nature, our analysis relies on traditional logit regressions (Hosmer, Lemeshow, and Sturdivant 2013). Consequently, we estimate the probability of the act or intention to switch by employing the following empirical model:

$$P(Y^i_{jk} = 1|H_{jk},\ E_k,\ C_{jk}) = \frac{1}{1 + e^{-(\alpha+\beta(H_{jk})+\varphi(E_k)+\gamma(C_{jk}))}} \qquad (1)$$

Two variants ($i \in \{1, 2\}$) of the dependent variable $Y^i$ are used in the main analysis and the robustness check section, representing either *Cashless Switch* or *Cashless Intention*. Depending on the value of $i$, the outcome $Y^i = 1$ indicates that the person either switched to cashless payments or wishes to do so in the future; $H_{jk}$ is the vector that measures the characteristics, perceptions, and confidence in using technology of person $j$ living in country $k$; $E_k$ is a vector of specific characteristics of country $k$; while $C_{jk}$ is our core vector of COVID-19-induced fears and changes in the behavior of person $j$ living in country $k$.

Our sampling uses stratification by age, gender, and size of locality, and the survey spans 22 European countries. However, the sample size in each of the nations is not necessarily proportional to its population of Internet users. To remedy this issue methodologically, we proceed to calculate the actual proportions of Internet users for each country and, in our estimation, we weight each observation by the inverse of its probability of being sampled. In other words, the higher the weighting, the higher the observation's contribution to the residual sum of squares. Such an approach is commonly used in the literature (see, for instance, Moro et al. 2020). We note in passing that unweighted estimation results lead to identical conclusions regarding the processes being modeled.

Since the standard variance-covariance matrix is no longer appropriate, we use a sandwich (White 1980) estimator to compute it.

Robust estimation of standard errors is relied upon to deal with heteroskedasticity issues. When fitting the regressions, we take necessary precautions to avoid multicollinearity problems. This is accomplished by performing factor analysis that aggregates cognate questionnaire items into a construct. Most notably, we consider two factors representing the change in habits related to the COVID-19 epidemic, which have the potential to explain the curbed appetite for cash and transcend purely fear-based rationalization.

## 4. Data

Collection of the data used in this study was supported by a research grant awarded by the Polish National Science Centre and was implemented by a research agency, Interactive Research Center. The source data were obtained from consumers through a survey based on computer-assisted web interviews (CAWI), which utilized an interactive Internet questionnaire. Internet users were invited to register their interest in participating through e-mail and advertising campaigns. Those who volunteered collected points that were redeemable for prizes. Survey respondents were then selected through stratified sampling from the pool of registrants. Such a data collection approach permitted us to obtain a large sample in a relatively cost-effective manner. The interactive nature of the survey afforded us the opportunity to incorporate additional clarifications and definitions of the technical terms that could be accessed by respondents without the need to exit the webpage. CAWI also allowed participants to pause and save the answers that have already been submitted, facilitating thereby the process of consulting external information sources whenever needed.

The data collection exercise was preceded by a pilot study involving 230 respondents from 22 countries. The overriding aim of this undertaking was to verify whether respondents understand and interpret the questionnaire items correctly. Minor irregularities that were identified in the questionnaire were subsequently rectified and there was no need to conduct a second pilot study. The final sample, collected during the period spanning July to August 2020, includes 5,504 respondents from 22 European countries (Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, United Kingdom). According to Eurostat (2020), the number of Internet users in those countries accounted for 96 percent of all Internet users in the European Union in 2019.

Our survey was conducted online as, due to the pandemic, conducting face-to-face interviews would not have been possible. Since only individuals with Internet access could participate, this raises a question of whether our sample is sufficiently representative of the entire population in terms of the problem studied. To assess the gravity of this problem, we collect Eurostat data on the prevalence of Internet use in the countries of interest. The country-level statistics (presented in Appendix A) were subsequently weighted by population (taken from the World Development Indicators, WDI, database) to arrive at a sample average. The 2020 statistics indicate that proportion of individuals who used Internet in the last 12 months was 90.5 percent, while the proportion of people who have ever used it stood at 92.0 percent. Fortunately, the issue of potential non-representativeness may be even less significant than these statistics would indicate for reasons elucidated in Grewenig et al. (2023). They show that although it may be possible that onliners and offliners differ in their answering behavior, once both groups are interviewed in the face-to-face mode and individuals' background/demographic characteristics are controlled for, the statistical differences between the groups evaporate. We would like to note that our regressions account for demographic factors, which is likely to reduce the size of any possible bias arising from sampling to a tolerable level.

The data collection process employed stratified random sampling, with age, gender, and size of the respondent's locality acting as stratification factors. The stratification factors of gender, age, and size of locality are also used as controls in our regressions. Another control variable employed is the attitude towards privacy, which was quantified through a questionnaire item stating: "I prefer payments for shopping to be anonymous, so that no one can see what I bought and when." The possession of a card, mobile, or wearable that could be used at the point of sale is captured by the dummy variable *Cards & Mobile.* Individuals who are lacking such items face higher costs of switching to cashless technologies, in that they may be forced to open a bank account or acquire the requisite device. We also consider eight other variables that measure the respondents' perceptions, experience, technological literacy, and habits and that are built up as constructs using principal component factor analysis (Hair et al. 2013). Each of these constructs includes many highly correlated items that cannot be modeled separately due to multicollinearity problems.

The first set of factors examines the assessment of alternative cashless payment methods, namely NFC (or near-field communication) contactless payments like Google Pay, Apple Pay, or payments with wearables (smartwatches, smartbands), and QR (quick response) code payments. Each payment method is assessed across several dimensions using a five-point Likert scale, and one factor for each of the dimensions is subsequently extracted. These factors are labeled as *Convenience of Cashless Payments*, *Safety of Cashless Payments*, *Access to Cashless Payments Technologies, Ease of Use of Cashless Technologies*, and *Control over Finance with Cashless Payments.* Familiarity with technologies was encapsulated in three additional factors. The first one, called *Literacy in Using Mobile Apps*, is based on five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity. Moreover, we measure experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE (host card emulation, or mobile contactless in a card-issuer app). Principal component analysis suggests extraction of two factors (eigenvalues of 2.91 and 1.18) that are subsequently rotated using varimax rotation. The items that load clearly in one factor measure *Experience in Using Computer Payments*, while the second factor captures *Experience in Using Mobile Payments.*

Furthermore, our questionnaire comprised a series of items pertaining to habit formation during the pandemic. These items were prefaced by a request to provide an assessment of how the respondent's life will change one year after the COVID-19 pandemic is over, as compared to the time before it started. Responses to these questions were recorded on a five-point Likert scale. The first variable measured the impact of the pest on working habits ("I will work more remotely"), while the second one was designed to capture a possible increase in online activity as a substitute for physical contact

("I will meet people online more frequently"). We also endeavored to explore a shift in traveling patterns ("I will travel less in my country" and "I will travel less abroad"), as well as dining habits ("I will eat more frequently at home"). Finally, we evaluated whether COVID-19 affected personal perception of health ("I will be more focused on my health") and shopping preferences ("I will buy more online"). Two factors with eigenvalues of 2.97 and 1.01 are extracted from these predictions of future habits. The items that load clearly on the first factor capture *Change in Habits Related to Physical Contact*, while the second one clearly gauges *Change in Online Habits*.

All of the eight above-mentioned factors created for the purpose of this study underwent a rigorous process of verification with respect to internal consistency and sampling adequacy. Statistics related to this verification are reported in Table 1. By default, each of the constructs has an eigenvalue above unity. Reassuringly, the Cronbach's alphas are consistently above the recommended threshold of 0.60. The Keiser-Meyer-Olkin test does not detect any sampling inadequacy requiring remedial action, and the proportion of variance explained by the factors appears to be satisfactory.

Moving away from factors, we explore another measure that is critical to our investigation. It intends to capture individual fear related to the possibility of contracting the disease through contact with cash. However, one needs to bear in mind that measurement must be done in relative terms. Respondents will be deterred from using cash for transitional purposes only if they perceive its infection risk to be higher than that for cashless instruments. For this reason, there was a need to include two items in the questionnaire which read "I am afraid of contracting COVID-19 due to the usage of cash in physical stores" and "I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores." By taking the difference between the responses to these two questions, we construct a variable called *Net Fear of Cash*. Since the original items were measured on a five-point scale, the resultant net fear variable ranges from $-4$ to $+4$.

Finally, we utilize three variables that are measured at the country level. We include the cumulative number of COVID-19 deaths (in thousands) that occurred prior to July 2020 in order to consider the general impact that the pandemic had in a given country. Furthermore, the estimated size of the shadow economy in 2016 (as

**Table 1. Characteristics of Factors Used in the Study**

| Factor | Eigenvalue | Cronbach's Alpha | Proportion of Variance Explained | Kaiser-Meyer-Olkin Measure |
|---|---|---|---|---|
| *Convenience of Cashless Payments* | 3.6510 | 0.8665 | 0.7302 | 0.8751 |
| *Safety of Cashless Payments* | 3.9730 | 0.9346 | 0.7945 | 0.8897 |
| *Access to Cashless Payments Technologies* | 3.7631 | 0.9161 | 0.7526 | 0.8735 |
| *Ease of Use of Cashless Technologies* | 3.8451 | 0.9236 | 0.7690 | 0.8774 |
| *Control over Finance with Cashless Payments* | 4.1703 | 0.9495 | 0.8341 | 0.8968 |
| *Literacy in Using Mobile Apps* | 2.3729 | 0.7208 | 0.4746 | 0.7818 |
| *Experience in Using Computer Payments*<br>*Experience in Using Mobile Payments* | 2.1871<br>1.9133 | 0.6027 | 0.3701 | 0.8265 |
| *Change in Habits Related to Physical Contact*<br>*Change in Online Habits* | 2.9795<br>1.0172 | 0.7722 | 0.5710 | 0.8265 |

a percentage of GDP) was considered as an explanatory variable for cash preferences arising from tax evasion and illegal activities. These estimates were sourced from Kelmanson et al. (2019). Lastly, we create a variable measuring the number of EFT-POS terminals per 1,000 inhabitants in 2020 based on the data published by Bank for International Settlements (2022), ECB (2022), and Norges Bank (2020).[1]

Table 2 provides definitions of all the variables used in the study, while Table 3 reports the corresponding summary statistics. Evaluation of these statistics paints a picture of the individuals involved in our survey. An average respondent resided in a city with less than 100,000 inhabitants and was 47 years of age. The latter figure was influenced by the fact that people under the age of 18 were not invited to participate. Women constituted 52 percent of the sample, which is representative of the broader population in the countries of interest. On average, those who were surveyed showed a slight preference towards payment anonymity but tended to pay primarily with cards and mobiles at the point of sale. When analyzing Table 3, one needs to bear in mind that all the constructs created through factor analysis have a mean of zero and a standard deviation of one.

Importantly, 41 percent of people declared that they use cashless payments more often during the COVID-19 crisis, while 47 percent stated that they will use cashless payments more frequently after the pandemic is over. An average respondent believed that the risk of contracting the coronavirus is slightly higher for cash than the cashless alternatives. Appendix B provides more detailed data in this regard by presenting a breakdown of the key variables by country. Judging from these statistics, respondents who were most keen to switch from cash to digital payments during the pandemic resided in the United Kingdom, Belgium, Ireland, and Portugal. In those countries, people were also more likely to declare their intention to further increase the frequency of cashless payments after the pandemic has been eradicated. Such behavior could be explained by the above-average fear of virus transmission through cash as compared

[1]Since the 2020 data had two missing observations (Bulgaria and Norway), we resorted to using 2019 figures for these two countries. In our judgment, this is a sensible solution since the state of the payment infrastructure does not change rapidly on a year-to-year basis.

**Table 2. Definitions of Variables**

| Variable | Definition |
|---|---|
| *Cashless Switch* | A binary variable taking the value of one for the response "Yes, I pay more often cashless (by card, smartphone, smartwatch)" to the questionnaire item "Has the coronavirus pandemic (COVID-19) affected how you pay in physical stores?". The responses "Yes, I pay more cash," "Not affected (I pay the same way as I did before pandemic," "I do not know," and "I did not make any purchases during pandemic" are coded as zero. |
| *Cashless Intention* | Dummy variable measuring respondent's agreement with the statement "After the pandemic, I will use cashless payments more often" (1 = yes, 0 = no) |
| *Gender* | Dummy variable capturing respondent's gender (1 if female, 0 otherwise) |
| *Location Size* | Response to a question regarding the size of the location (including suburbs) where the respondent lives. Responses are coded on a six-point scale:<br>1 – Rural area<br>2 – City with less than 50,000 inhabitants<br>3 – City between 50,000 and 100,000 inhabitants<br>4 – City between 100,000 and 500,000 inhabitants<br>5 – City between 500,000 and 1,000,000 inhabitants<br>6 – City over 1,000,000 inhabitants |
| *Age* | Age of the respondent |
| *Cards & Mobile* | A dummy variable measuring the possession of any card, mobile, or wearable applicable at the point of sale (1 = yes, 0 = no) |
| *Anonymity* | Degree of agreement with a statement "I prefer payments for shopping to be anonymous, so that no one can see what I bought and when" measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) |
| *Convenience of Cashless Payments* | A factor aggregating assessments of convenience of five different cashless payment technologies (contactless (NFC) payments, Google Pay, Apple Pay, QR code payments, contactless payments with wearables) |
| *Safety of Cashless Payments* | A factor combining perceptions of safety of five different cashless payment technologies |
| *Access to Cashless Payments Technologies* | A factor aggregating assessments of how widespread five different cashless payment instruments are |
| *Ease of Use of Cashless Technologies* | A factor extracted from evaluations of how easy to use five cashless payment technologies are |

(*continued*)

**Table 2. (Continued)**

| **Variable** | **Definition** |
|---|---|
| *Control over Finance with Cashless Payments* | A factor constructed from an assessment of how much control over personal finance is afforded by five different cashless payment technologies |
| *Literacy in Using Mobile Apps* | A factor aggregating five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity |
| *Experience in Using Computer Payments* | First factor extracted from the items measuring respondent's experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to computer-based payments. |
| *Experience in Using Mobile Payments* | Second factor extracted from the items measuring respondents' experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to mobile-based payment technologies. |
| *Change in Habits Related to Physical Contact* | First factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," " I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to physical contact. |
| *Change in Online Habits* | Second factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," " I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to online habits. |
| *Net Fear of Cash* | A variable constructed by taking the difference in responses to two questionnaire items: "I am afraid of contracting COVID-19 due to the usage of cash in physical stores" and "I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores." |
| *COVID Deaths* | Total number of COVID-19 deaths (in thousands) for the country in which the respondent resides |
| *Shadow Economy* | Size of the shadow economy as a percentage of GDP in the respondent's country of residence |
| *Number of EFT-POS Terminals per Thousand People* | Number of terminals provided by resident payment service providers per thousand inhabitants |

## Table 3. Summary Statistics

| Variable | Mean | Standard Deviation | Minimum | 25th Percentile | Median | 75th Percentile | Maximum |
|---|---|---|---|---|---|---|---|
| *Cashless Switch* | 0.47 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *Cashless Intention* | 0.41 | 0.49 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *Gender* | 0.52 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| *Location Size* | 2.77 | 1.57 | 1.00 | 1.00 | 2.00 | 4.00 | 6.00 |
| *Age* | 47.04 | 16.31 | 18.00 | 33.00 | 47.00 | 62.00 | 100.00 |
| *Cards & Mobile* | 0.90 | 0.30 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| *Anonymity* | 3.28 | 1.12 | 1.00 | 3.00 | 3.00 | 4.00 | 5.00 |
| *Convenience of Cashless Payments* | 0.00 | 1.00 | –2.05 | –0.45 | –0.06 | 0.67 | 1.94 |
| *Safety of Cashless Payments* | 0.00 | 1.00 | –2.29 | –0.21 | –0.02 | 0.80 | 1.88 |
| *Access to Cashless Payments Technologies* | 0.00 | 1.00 | –2.37 | –0.36 | –0.14 | 0.56 | 2.09 |
| *Ease of Use of Cashless Technologies* | 0.00 | 1.00 | –2.59 | –0.45 | –0.07 | 0.62 | 1.70 |
| *Control over Finance with Cashless Payments* | 0.00 | 1.00 | –2.36 | –0.29 | –0.29 | 0.74 | 1.78 |
| *Literacy in Using Mobile Apps* | 0.00 | 1.00 | –0.88 | –0.88 | –0.31 | 0.52 | 2.42 |
| *Experience in Using Computer Payments* | 0.00 | 1.00 | –1.36 | –0.20 | –0.20 | –0.20 | 9.66 |
| *Experience in Using Mobile Payments* | 0.00 | 1.00 | –2.97 | –0.52 | –0.52 | 0.43 | 5.90 |
| *Change in Habits Related to Physical Contact* | 0.00 | 1.00 | –2.93 | –0.53 | –0.02 | 0.61 | 2.56 |
| *Change in Online Habits* | 0.00 | 1.00 | –3.64 | –0.59 | 0.16 | 0.68 | 3.19 |
| *Net Fear of Cash* | 0.24 | 1.01 | –4.00 | 0.00 | 0.00 | 0.00 | 4.00 |
| *COVID Deaths* | 8.49 | 5.18 | 2.47 | 4.99 | 6.25 | 11.48 | 20.98 |
| *Shadow Economy* | 21.98 | 7.18 | 9.60 | 16.70 | 20.30 | 27.80 | 37.80 |
| *Number of EFT-POS Terminals per Thousand People* | 30.35 | 13.97 | 13.18 | 23.01 | 26.79 | 32.99 | 71.11 |

**Note:** Definitions of the variables can be found in Table 1. The number of observations for each of the variables listed above is 5,504.

to cashless alternatives as well as significant shifts in habits spanning both the physical and virtual realms.

Another point of interest is the joint distribution of the two dependent variables in our study. The data reported in Appendix C reveals that the values of *Cashless Switch* and *Cashless Intention* coincide for 70.35 percent of respondents. This is unsurprising, as these variables are expected to have common covariates. When we partition our sample based on the values of the two dependent variables, we discover that significant differences in the average value of *Net Fear of Cash* emerge across different subgroups. This preliminary result indicates that the fear of infection through handling physical currency is determining payment behavior.

## 5. Empirical Results

Table 4 presents the results of weighted logit regressions estimating the likelihood of an immediate increase in the frequency of cashless payments in response to the COVID-19 pandemic. The first specification focuses on the fear of contagion via cash, while the second one considers the impact of changing habits. Regression (3) subsumes both these determinants as well as a full set of controls, making it the most comprehensive model amongst the considered alternatives. With respect to the key explanatory variables, our empirical findings cohere with a priori predictions. *Net Fear of Cash* is positively signed and exhibits a strong statistical significance. Clearly, individuals who believe that handling cash poses a relatively serious health hazard tend to enthusiastically embrace cashless instruments. The $t$-statistics associated with the variable *Change in Habits Related to Physical Contact* exceed the value of 10, making it another strong predictor of payment behavior. In other words, respondents who declared an intention to alter their routines in the physical world were ceteris paribus more likely to use cashless payment methods at the point of sale. *Change in Online Habits* appears to be a further important explanatory factor, albeit the magnitude of its coefficient and its explanatory power pales in comparison to the *Change in Habits Related to Physical Contact*. One may therefore argue that, when it comes to choices of payment technologies, habits in the physical sphere are of greater consequence than those in the virtual realm.

## Table 4. Modeling the Switch to Cashless Payments during the Pandemic

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1764** | 0.1528** | 0.1597** |
| | (0.0762) | (0.0774) | (0.0778) |
| *Location Size* | 0.0265 | 0.0150 | 0.0189 |
| | (0.0249) | (0.0253) | (0.0255) |
| *Age* | 0.0047* | 0.0066** | 0.0063** |
| | (0.0025) | (0.0026) | (0.0026) |
| *Cards & Mobile* | 0.6695*** | 0.7438*** | 0.7286*** |
| | (0.1323) | (0.1334) | (0.1336) |
| *Anonymity* | –0.0560* | –0.1230*** | –0.1082*** |
| | (0.0335) | (0.0346) | (0.0349) |
| *Convenience of Cashless Payments* | 0.0079 | –0.0261 | –0.0210 |
| | (0.0534) | (0.0559) | (0.0560) |
| *Safety of Cashless Payments* | 0.1188** | 0.1245** | 0.1140* |
| | (0.0594) | (0.0598) | (0.0604) |
| *Access to Cashless Payments Technologies* | 0.0247 | –0.0431 | –0.0360 |
| | (0.0535) | (0.0547) | (0.0552) |
| *Ease of Use of Cashless Technologies* | 0.1515** | 0.1707*** | 0.1600*** |
| | (0.0601) | (0.0616) | (0.0617) |
| *Control over Finance with Cashless Payments* | 0.0107 | –0.0210 | –0.0244 |
| | (0.0530) | (0.0536) | (0.0544) |
| *Literacy in Using Mobile Apps* | 0.3763*** | 0.3655*** | 0.3630*** |
| | (0.0467) | (0.0469) | (0.0472) |
| *Experience in Using Computer Payments* | 0.0631* | 0.0166 | 0.0219 |
| | (0.0361) | (0.0369) | (0.0373) |
| *Experience in Using Mobile Payments* | 0.0420 | 0.0172 | 0.0195 |
| | (0.0442) | (0.0460) | (0.0457) |
| *COVID Deaths* | 0.0245*** | 0.0174** | 0.0183** |
| | (0.0072) | (0.0074) | (0.0075) |
| *Shadow Economy* | –0.0132** | –0.0192*** | –0.0201*** |
| | (0.0057) | (0.0058) | (0.0058) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0031 | 0.0002 | 0.0011 |
| | (0.0025) | (0.0025) | (0.0026) |
| *Net Fear of Cash* | 0.2812*** | | 0.2431*** |
| | (0.0389) | | (0.0399) |
| *Change in Habits Related to Physical Contact* | | 0.4748*** | 0.4526*** |
| | | (0.0421) | (0.0422) |
| *Change in Online Habits* | | 0.0981** | 0.0984** |
| | | (0.0392) | (0.0394) |
| Constant | –1.0736*** | –0.6432** | –0.7457** |
| | (0.2822) | (0.2883) | (0.2907) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 343.0 | 391.3 | 429.5 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.0885 | 0.108 | 0.117 |

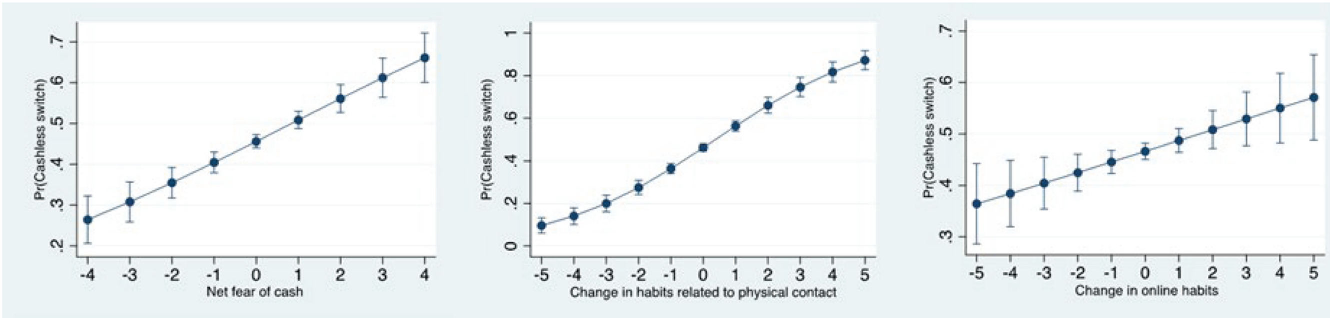
**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

While the statistical significance of fear and habits is unequivocal, the question arises as to the economic significance of our results. To probe this issue, we plot predictive functions in panel A of Figure 1. More specifically, these plots show the expected probability of *Cashless Switch* = 1 when one key independent variable is varied, and the remaining regressors are kept constant at the sample average value. When interpreting the values on the horizontal axis, one needs to remember that *Net Fear of Cash* was derived from differencing two five-point Likert scales, while a unitary move across the x-axis for the habit variables denotes a change equivalent to one standard deviation. Clearly, probabilities are increasing monotonically with all three of the variables considered in panel A, with the increase being remarkably steep for *Net Fear of Cash* and *Change in Habits Related to Physical Contact*. Judging from the plots, these two factors were decisive for many respondents in their decision to abandon cash payments at POS during the COVID-19 crisis.

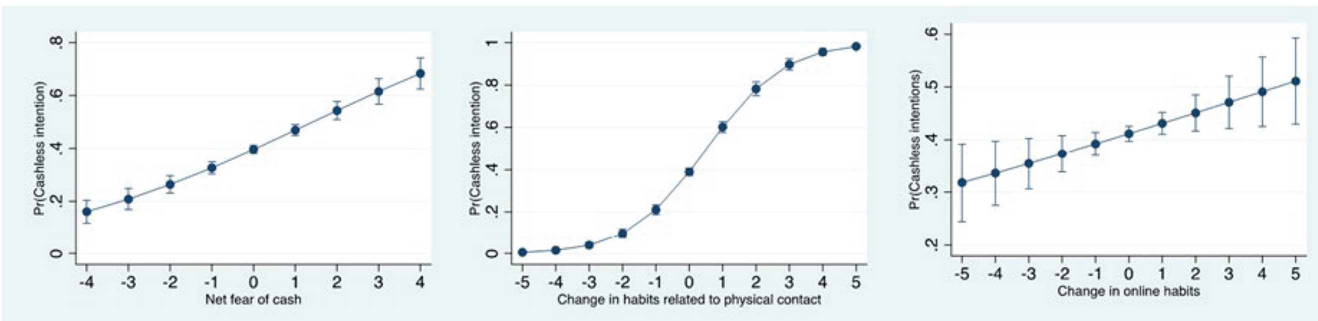
The influence of statistically significant control variables warrants further discussion. Females and those who are literate in using mobile apps showed greater proclivity to embrace cashless technologies. Unsurprisingly, those without access to cashless instruments remained dependent on banknotes and coins during the COVID crisis. Since older individuals face higher SARS-CoV-2 fatality rates (O'Driscoll et al. 2021), their health risk arising from engagement in cash-based transactions is graver. Cognizant of this reality, older people relinquished payments with physical currency more readily. Apprehension over anonymity issues and the influence of shadow economy thwarted individuals' transition towards cashless transacting. Respondents with no concerns over safety of digital payment technologies were more likely to use them frequently, which mirrors the argument of Ostlund (1974) that the perceived risk of an innovation hinders its diffusion. Furthermore, in line with the theoretical predictions of the technology acceptance model of Davis (1989), perceived ease of use of cashless instruments correlated positively with their adoption. Lastly, the number of COVID-related deaths in the respondent's country of residence was a factor contributing to the abandonment of cash. The number of deaths captures general concern over the pandemic, which goes beyond change in habits and fear of using cash captured by other variables in the model.

**Figure 1. Marginal Effects for the Key Explanatory Variables**

A. Estimates from the *Cashless Switch* Model




B. Estimates from the *Cashless Intention* Model




**Note:** The plots show a prediction of probability that either *Cashless Switch* = 1 (panel A) or *Cashless Intention* = 1 (panel B) when one of the key explanatory variables is changed, while the remaining explanatory variables are kept constant at the sample average level. The vertical bars represent 95 percent confidence intervals. The graphs in panel A are derived based on logit regression (3) in Table 4, while panel B relied on regression (3) in Table 5.

Table 5 reports weighted logit estimates for models considering the intention to use more cashless transactions after the COVID-19 pandemic is over. The results indicate that COVID-induced fear of cash may have a long memory and is likely to extend into the distant future. Once again, *Change in Habits Related to Physical Contact* exhibits stronger statistical significance and has a larger marginal effect than *Change in Online Habits* (see panel B of Figure 1). Juxtaposition of the results with those contained in Table 4 reveals that the coefficients on the fear and change in habits variables are notably larger, which coheres with our expectations. Table 4 models actual changes in behavior, while Table 5 considers reported intentions to alter behavioral patterns in the future. Since forming an intention requires less effort on the part of the respondent than taking an actual action, the parameter estimates in Table 5 are expected to be larger.

Broadly speaking, a similar pattern of significance emerges across control variables. A slight discrepancy that could be noted is the weaker explanatory power of *Age* and *Shadow Economy.* It appears that older people, who are in the highest risk group, may be reluctant to increase the frequency of their cashless payments relative to the pandemic level after the health perils have dissipated. The diminished statistical significance of the shadow economy could reflect the fact that its future size is essentially unknown and, consequently, this variable plays a smaller role in shaping intentions. The protracted pandemic is expected to have a disproportionate effect on the informal economy, where workers without formalized contracts lack job security and do not benefit from furlough schemes (Webb, McQuaid, and Rand 2020).

The economic significance of the control variables can be assessed using the average marginal effects reported in our Appendix D. What can be gleaned from these estimates is that the variable with the most pronounced economic impact is *Cards & Mobile*, regardless of whether we model the *Cashless Switch* or *Cashless Intention.* The average marginal effect for *Literacy in Using Mobile Apps* proved large for the instantaneous increase in cashless payment frequency during the pandemic but was notably attenuated in the regression considering post-pandemic payment intentions. What mattered more from the point of view of agreement with the statement "After the pandemic, I will use cashless

**Table 5. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1980** | 0.1606* | 0.1772** |
| | (0.0787) | (0.0829) | (0.0843) |
| *Location Size* | 0.0256 | 0.0081 | 0.0133 |
| | (0.0252) | (0.0270) | (0.0272) |
| *Age* | 0.0023 | 0.0054* | 0.0046 |
| | (0.0026) | (0.0029) | (0.0029) |
| *Cards & Mobile* | 0.5743*** | 0.7547*** | 0.7324*** |
| | (0.1431) | (0.1424) | (0.1438) |
| *Anonymity* | 0.0087 | –0.1326*** | –0.1125*** |
| | (0.0346) | (0.0384) | (0.0391) |
| *Convenience of Cashless Payments* | 0.0699 | 0.0233 | 0.0290 |
| | (0.0554) | (0.0613) | (0.0620) |
| *Safety of Cashless Payments* | 0.2486*** | 0.2768*** | 0.2715*** |
| | (0.0629) | (0.0693) | (0.0700) |
| *Access to Cashless Payments Technologies* | 0.0520 | –0.0876 | –0.0789 |
| | (0.0569) | (0.0639) | (0.0651) |
| *Ease of Use of Cashless Technologies* | 0.1901*** | 0.2330*** | 0.2137*** |
| | (0.0635) | (0.0707) | (0.0717) |
| *Control over Finance with Cashless Payments* | 0.1214** | 0.0696 | 0.0714 |
| | (0.0543) | (0.0595) | (0.0609) |
| *Literacy in Using Mobile Apps* | 0.1517*** | 0.1288** | 0.1197** |
| | (0.0469) | (0.0508) | (0.0514) |
| *Experience in Using Computer Payments* | 0.1186*** | 0.0361 | 0.0467 |
| | (0.0396) | (0.0410) | (0.0426) |
| *Experience in Using Mobile Payments* | 0.0692 | 0.0314 | 0.0354 |
| | (0.0458) | (0.0481) | (0.0485) |
| *COVID Deaths* | 0.0284*** | 0.0169** | 0.0187** |
| | (0.0074) | (0.0077) | (0.0077) |
| *Shadow Economy* | 0.0105* | –0.0012 | –0.0021 |
| | (0.0059) | (0.0062) | (0.0063) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0005 | –0.0049* | –0.0036 |
| | (0.0025) | (0.0027) | (0.0028) |
| *Net Fear of Cash* | 0.4408*** | | 0.3955*** |
| | (0.0438) | | (0.0472) |
| *Change in Habits Related to Physical Contact* | | 1.0063*** | 0.9847*** |
| | | (0.0547) | (0.0551) |
| *Change in Online Habits* | | 0.1071** | 0.1098** |
| | | (0.0441) | (0.0452) |
| Constant | –1.8385*** | –1.0840*** | –1.2423*** |
| | (0.2908) | (0.3040) | (0.3115) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 395.6 | 537.4 | 550.6 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.123 | 0.205 | 0.223 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

payments more often" was the safety of the cashless payment instruments.

## 6. Robustness Checks and Further Results

In order to confirm the validity of the story presented here, further tests and robustness checks were performed. To start with, we experimented with a different constellations and definitions of control variables. Firstly, the variable *Cards & Mobile* measuring the possession of any card, mobile, or wearable applicable at the point of sale was replaced with dummy variables categorizing respondents in accordance with their historical cash usage. The results displayed in Appendix E reveal a rational pattern of behavior. Individuals who made all of their transactions in cash prior to the pandemic were least likely to increase their frequency of cashless payments and showed least inclination to do so in the future. This is unsurprising, as the group includes people who operate in the shadow economy, are financially excluded, or have strong desire for anonymity. These attributes firmly anchor individuals' desire to transact in cash. For the most part, the group that was most motivated to embrace more cashless transactions comprised respondents who historically used cash in 1 percent to 30 percent of their payments. Most importantly, inclusion of the past payment behavior dummies did not change our main conclusions regarding the key explanatory variables.

Secondly, we redefined our measurements of the five attributes of cashless payments (convenience, safety, access, ease of use, and control over finance). Instead of gauging them in absolute terms, we expressed them relative to the perceived characteristics of cash. Appendix F displays our findings which, once again, reaffirm the significance of fear and habit shifts in the formation of payment preferences.

Thirdly, we interrogated the question of whether the effect of the *Age* variable is linear. To this end, we converted the continuous *Age* variable into age-group dummies, which should allow us to pinpoint the age brackets in which respondents were particularly sensitive to COVID concerns (see Appendix G). The results indicate that individuals aged between 60 and 69 were particularly eager to increase the frequency of their cashless payments during the pandemic. Perhaps this could have been attributed to the fact that

COVID mortality within this age group was higher as compared to younger people. In terms of declaring an intention to increase frequency of cashless payments after the pandemic is over, respondents between the ages of 40 to 59 were particularly reluctant to do so.

Another point of inquiry arose from the reflection that respondents who already transacted exclusively cashless in the pre-pandemic period would have the tendency to rate different aspects of such transactions highly. At the same time, they were unable to increase their frequency of cashless payments, as they already resided at the limit. A question therefore arises as to whether our results are sensitive to the exclusion of such individuals. To probe this issue further, we constructed a sample which eliminated people who did not use cash at all in the 12 months preceding the survey ($n = 363$). We rerun the logit regressions on the restricted sample (see Appendix H) and note that our main inferences regarding the three key explanatory variables remain unaltered.

In the next step of our exploration, we investigated whether there are any country-specific factors that moderate the relationship between the COVID pandemic and respondents' willingness to switch to cashless transactions. For this purpose, we created eight dummies that were subsequently interacted with the three key explanatory variables in our study (*Net Fear of Cash* and the two change-in-habits variables). These dummies indicated countries with above-median values recorded for the EFT-POS terminals per thousand people, shadow economy size, COVID deaths, power distance and uncertainty avoidance index from the Hofstede national culture database, GDP per capita expressed in purchasing power parity prices, COVID stringency index measuring the severity of government policy responses, and countries that are Scandinavian. The estimates of logistic regressions imparting these interaction terms, along with their interpretation, are shown in Appendix I.

Finally, we consider an alternative approach to modeling our dichotomous variables by employing weighted probit models. Compared to the logit regressions used in our baseline regressions, this methodological framework makes different assumptions about the error term and is based on a different link function. Reassuringly, our results from this estimation reported in Appendix J corroborate our earlier conclusions, which is a testament to the fact that our inferences are not a mere byproduct of the methodology selected.

## 7. Practical Considerations

The first sphere that could be affected by the collective switch to cashless transactions is the banking sector. Such shift is positively affecting the profitability of banks in at least two ways. Firstly, payment services are an enduring element embedded in the core operations of commercial banks (Rambure and Nacamuli 2008) and allow them to augment and diversify their revenue streams. Historically, banks derived most of their revenues from acting as intermediaries that take deposits and lend money, earning net interest spread in the process. However, over time, non-interest income[2] became increasingly important (DeYoung and Rice 2004). Among the non-interest revenue streams are those attributable to processing and clearing payment transactions for various parties (Radecki 1999). According to the Federal Deposit Insurance Corporation (FDIC) about 33 percent of U.S. banks' income was classed as non-interest (Li et al. 2021). McKinsey and Company (2022) report that global payments revenues totaled \$2 trillion in 2019, increasing to \$2.1 trillion in 2021. These figures translate into a rise in the share of banking revenues from about 39 percent to 40 percent.

Secondly, adoption of electronic payment instruments bestows additional benefits upon banks in the form of reduced operating expenses, because the cost of electronic payment equals about one-third to one-half of the paper-based equivalent (Humphrey et al. 2006). Electronic payments are subject to economies of scale, which play a significant role in the unit costs of transactions incurred by banks (Beijnen and Bolt 2009; Bolt and Humphrey 2007; Khiaonarong 2003). These bank incentives are evinced by the rise of cashless branches in which withdrawals, deposits, or check-cashing services are unavailable (Engert and Fung 2019). Emergence of such bank offices is especially conspicuous in Sweden, where about 60 percent of branches had become cashless by 2016, forcing an even greater reduction in cash usage (Engert, Fung, and Segendorf 2020).

For FinTech firms (that is, innovative, technological companies providing financial services) change of payment habits could also have profound impact. Not only do they profit from launching

[2] That is, income arising from sources unconnected to the collection of interest payments (Haubrich and Young 2019).

and operationalizing digital payment innovations, but they are also actively involved in credit markets. Ghosh, Vallee, and Zeng (2021) argue that FinTechs consider cashless payments to be a good source of verifiable information regarding the creditworthiness of a borrower, which forces the prospective loan applicants to adopt them. The customer payment data is leveraged for alternative credit underwriting models in a novel way, creating economic incentives to move away from cash.

Global consultancy firm KPMG (2020) estimates that $361 billion was invested in FinTechs during the 2017–19 period and 58 of those companies hit a valuation of more than $1 billion, becoming so-called unicorns (McKinsey and Company 2020a). The momentous rise of FinTechs and their impact on transforming the financial industry's landscape is undisputed (Gomber et al. 2018; Thakor 2020). Interestingly, about $144.4 billion of the above-mentioned total investment was channeled to companies providing payment services. These companies are referred to as PayTechs and compete with banks for their non-interest revenue streams. The population of PayTechs is growing continuously, with the number of companies that obtained regulatory licenses to provide such services in the European Union soaring from 350 in 2017 to 1,475 in 2020 (Polasik et al. 2020).

Evidence also seems to point to a surge in demand for products offered by FinTech and PayTech companies during the COVID-19 crisis. According to McKinsey and Company (2020b), 6 percent of U.S. consumers opened an overall banking FinTech account during the pandemic, while Fu and Mishra (2022) report a significant rise in downloads of finance mobile apps from Google and Apple app stores during this period. Interestingly, the epidemic-induced uptick in FinTech solutions was not uniformly distributed across countries, with a number of players in the sector struggling to raise funds and balancing precariously on the edge of insolvency (see, for instance, Chernova 2019; Kelly 2020; Kodoth 2020).

Our empirical analysis could be valuable to the banking sector, as well as FinTech and PayTech firms, because it provides a clear guidance for their future marketing efforts. More specifically, it helps to identify groups that are likely to use cashless payment services more frequently in the future and pinpoint attitudes that tend to promote such behavior. Firstly, our findings indicate that women declared their willingness to increase the frequency of cashless payments more often than men. Advertising campaigns should be tailored accordingly to take full advantage of this fact. Furthermore, any promotions of digital payment instruments should endeavor to reassure the users about their safety. Our respondents attached great importance to this attribute. Similarly, ease of use of digital payment technologies proves to be a powerful stimulus for their adoption. For this reason, a deliberate effort should be undertaken to make the design of payment instruments/applications more user-friendly, without compromising their safety. Any advertising initiatives should also take account of the lasting changes in habits induced by the COVID pandemic and could perhaps attempt to reliably educate about the risk of contracting the virus via handling cash.

Another interesting result reported in this paper relates to the fact that the existence of shadow economy hindered the transition towards digital payments during the COVID-19 period, although this relationship was weaker for the reported future intentions. Vigorous actions of tax authorities and law enforcement agencies aimed at curbing the underground economic activities could potentially foster a more rapid move towards a cashless society. For many years, the shadow economy was perceived to be closely linked to cash transactions (Gordon 1990). Similarly, reduction in cash payments could have a discouraging effect on tax evasion and criminal activities. Zhang et al. (2019) find that an increase in the use of cashless payments helps to shrink and transform the shadow economy, while Schneider (2019) estimates that complete elimination of cash would decrease its size by 20.1 percent. With respect to tax compliance, two studies focusing on Greece and the euro area by Hondroyiannis and Papaoikonomou (2017, 2020) showed that that an increase in the share of card payments in private consumption led to a corresponding growth in VAT (value-added tax) revenues. For Greece, a 1 percentage point rise in this share was estimated to augment the VAT receipts by somewhere between 1 percent (Hondroyiannis and Papaoikonomou 2017) and 1.4 percent (Danchev, Gatopoulos, and Vettas 2020). Studies exploring this issue from the perspective of the whole European Union (most notably Immordino and Russo 2018 and Madzharova 2020) cohere with the conclusion that cashless payments tend to reduce VAT tax evasion.

Changes in how people pay are also critical for central banks, as these institutions are sole issuers of money and play a key role in its distribution. As shown in Subsection 2.2, the share of cash payments in retail transactions has decreased worldwide and transactional use of cash plunged even further during the COVID-19 epidemic. This, however, was eclipsed by precautionary hoarding of cash, which led to an increase in the overall demand for money (see, for instance, Caswell et al. 2020; Chen et al. 2020; Goodhart and Ashworth 2020; Kotkowski 2023). Whatever the demand, central banks need to be ready to provide an adequate supply of physical money at all times, in addition to performing their role as monetary authorities and safeguarding the financial system (Restoy 2020). This issuing obligation is especially important during times of distress, such as the COVID-19 pandemic, because failure to meet the surge in demand could heighten reputational risk. Additionally, central banks must be aware that the elevated demand would not last forever, and that they may be forced to withdraw and redeem some of the cash that is currently in circulation (Snellman, Vesala, and Humphrey 2001).

## 8. Conclusions

The coronavirus epidemic instilled a widespread sense of apprehension and changed the trajectories of our lives. In this paper, we examined how the disease outbreak affected consumer choices regarding payment methods at the point of sale. The results clearly indicate that those who believed that cash poses a relatively high risk of viral transmission opted for cashless alternatives. Payment behavior was also indirectly transmuted through the impact that the pandemic had on the patterns of our daily activities. Especially, our altered habitual conduct in physical spaces exerted a powerful influence, steering individuals towards cashless transactions. The drift away from physical currency was also attributable to changes in online behavior, albeit to a lesser degree. Interestingly, the possibility of contagion through cash and transformed habits not only drove the contemporaneous switch between the payment instruments but also imprinted themselves on respondents' future intentions to transact in a cashless manner, even after the COVID pandemic has been contained.

Our findings have several practical implications relevant to every link in the chain of payment transaction processing. Banks, acquirers, FinTechs, and payment organizations must be aware that COVID-like events can drastically change the volume and value of processed transactions. While in some cases it may bring a much-needed revenue stream, it also puts a strain on available resources. Failure to meet the surge in demand could heighten reputational risk. Similarly, merchants need to show flexibility in times perturbed by fear of disease contagion and dynamically evolving consumer habits. Preferred payment options should be offered to paying patrons to alleviate their anxiety. Furthermore, central banks should carry out further studies on the epidemiological safety of different payment instruments, so conclusive knowledge about this phenomenon could emerge and potentially ease angst within the population. Finally, the COVID-induced speedy move towards digital payments has the potential to disadvantage those who are financially excluded, particularly immigrants, elderly, unemployed, or disabled people. This area of concern warrants further scientific inquiry in the future.

## Appendix A

### Table A.1. Internet Use in Our Sample Countries in 2020

| | Individuals Who Used Internet in the Last 12 Months (in %) | Individuals Who Have Ever Used the Internet (in %) | Population |
|---|---|---|---|
| Austria | 89 | 92 | 8,917,205 |
| Belgium | 92 | 94 | 11,555,997 |
| Bulgaria | 74 | 79 | 6,934,015 |
| Czech Republic | 89 | 92 | 10,698,896 |
| Denmark | 99 | 99 | 5,831,404 |
| Finland | 97 | 98 | 5,530,719 |
| France* | 91 | 93 | 67,391,582 |
| Germany | 95 | 96 | 83,240,525 |
| Greece | 79 | 80 | 10,715,549 |
| Hungary | 86 | 88 | 9,749,763 |
| Ireland | 92 | 94 | 4,994,724 |
| Italy | 81 | 84 | 59,554,023 |
| Lithuania | 84 | 86 | 2,794,700 |
| Netherlands | 95 | 96 | 17,441,139 |
| Norway | 98 | 99 | 5,379,475 |
| Poland | 85 | 87 | 37,950,802 |
| Portugal | 79 | 82 | 10,305,564 |
| Romania | 85 | 86 | 19,286,123 |
| Slovak Republic | 91 | 93 | 5,458,827 |
| Spain | 93 | 94 | 47,351,567 |
| Sweden | 97 | 98 | 10,353,442 |
| United Kingdom | 98 | 98 | 67,215,293 |
| Population-Weighted Average | 90.5035 | 92.0413 | |

*Due to the lack of data, we use 2019 statistics for France.

**Note:** Internet use data are sourced from Eurostat, while the population data come from WDI. Survey consists of all individuals aged 16 to 74. On an optional basis, some countries collect separate data on other age groups: individuals aged 15 years or less, aged 75 or more.

# Appendix B

## Table B.1. Country-Level Averages for the Key Variables

| | ***Cashless Switch*** | ***Cashless Intention*** | ***Net Fear of Cash*** | ***Change in Habits Related to Physical Contact*** | ***Change in Online Habits*** |
|---|---|---|---|---|---|
| Austria | 0.39 | 0.28 | 0.06 | –0.24 | –0.14 |
| Belgium | 0.63 | 0.48 | 0.32 | 0.01 | 0.08 |
| Bulgaria | 0.29 | 0.34 | 0.28 | 0.17 | 0.01 |
| Czech Republic | 0.43 | 0.35 | 0.25 | –0.15 | –0.02 |
| Denmark | 0.42 | 0.34 | 0.41 | –0.18 | –0.10 |
| Finland | 0.41 | 0.38 | 0.16 | –0.13 | –0.01 |
| France | 0.42 | 0.37 | 0.14 | –0.05 | 0.01 |
| Germany | 0.34 | 0.31 | 0.09 | –0.22 | –0.21 |
| Greece | 0.47 | 0.33 | 0.03 | –0.18 | 0.12 |
| Hungary | 0.34 | 0.39 | 0.37 | –0.10 | –0.21 |
| Ireland | 0.63 | 0.51 | 0.35 | 0.20 | 0.06 |
| Italy | 0.40 | 0.38 | 0.10 | 0.23 | –0.05 |
| Lithuania | 0.31 | 0.39 | 0.22 | –0.08 | 0.01 |
| Netherlands | 0.56 | 0.38 | 0.18 | –0.10 | 0.14 |
| Norway | 0.47 | 0.38 | 0.11 | –0.22 | –0.07 |
| Poland | 0.56 | 0.53 | 0.44 | 0.09 | 0.07 |
| Portugal | 0.61 | 0.57 | 0.31 | 0.35 | 0.07 |
| Romania | 0.55 | 0.55 | 0.39 | 0.43 | 0.00 |
| Slovakia | 0.39 | 0.33 | 0.23 | –0.15 | 0.08 |
| Spain | 0.49 | 0.48 | 0.04 | 0.23 | 0.03 |
| Sweden | 0.32 | 0.29 | 0.20 | –0.24 | –0.07 |
| United Kingdom | 0.65 | 0.53 | 0.30 | 0.17 | 0.14 |

## Appendix C. Exploring the Data

To investigate the issue of overlap in respondents' answers, we present in Table C.1 the data on joint distribution of the two dependent variables used in our study.

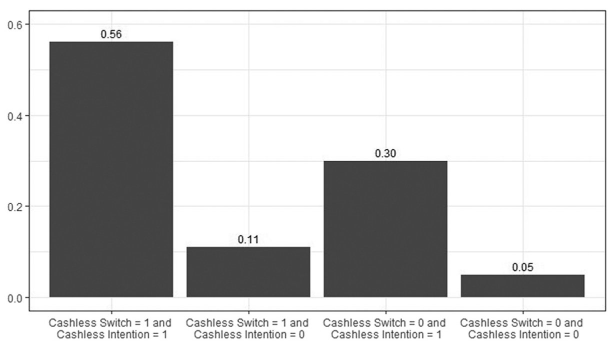
We have also examined whether the summary statistics for each of the four cohorts defined by the cells in the table above are comparable and have discovered the most pronounced differences occur for the variable *Net Fear of Cash*. Figure C.1 plots these values. This

**Table C.1. Joint Distribution of the Two Dependent Variables**

| | *Cashless Intention* = 0 | *Cashless Intention* = 1 | Total |
|---|---|---|---|
| *Cashless Switch* = 0 | 41.12% (2,263) | 12.17% (670) | 53.29% (2,933) |
| *Cashless Switch* = 1 | 17.48% (962) | 29.23% (1,609) | 46.71% (2,571) |
| Total | 58.59% (3,225) | 41.41% (2,279) | 100.00% (5,504) |

**Note:** This table presents the joint distribution of *Cashless Switch* and *Cashless Intention.* The numbers presented show the proportion of the sample and the number of observations falling within a particular category in parentheses.

**Figure C.1. Average *Net Fear of Cash* in Different Cohorts**




**Note:** This figure presents averages for the variable *Net Fear of Cash* in four groups defined by their values of *Cashless Switch* and *Cashless Intention.*

discovery aligns well with the story that is being told in our paper, namely that the fear of COVID transmission through cash drives the payment choices of respondents.

## Appendix D

### Table D.1. Average Marginal Effects for Control Variables

| | **Table 4 Column 3** | **Table 5 Column 4** |
|---|---|---|
| *Gender* | 0.0376 | 0.0387 |
| *Location Size* | 0.0051 | 0.0044 |
| *Age* | 0.0011 | 0.0007 |
| *Cards & Mobile* | 0.1521 | 0.1259 |
| *Anonymity* | –0.0160 | –0.0034 |
| *Convenience of Cashless Payments* | 0.0005 | 0.0125 |
| *Safety of Cashless Payments* | 0.0293 | 0.0549 |
| *Access to Cashless Payments Technologies* | 0.0043 | 0.0089 |
| *Ease of Use of Cashless Technologies* | 0.0365 | 0.0440 |
| *Control over Finance with Cashless Technologies* | 0.0041 | 0.0267 |
| *Literacy in Using Mobile Apps* | 0.0850 | 0.0346 |
| *Experience in Using Computer Payments* | 0.133 | 0.0236 |
| *Experience in Using Mobile Payments* | 0.0091 | 0.0141 |
| *COVID Deaths* | 0.0053 | 0.0056 |
| *Shadow Economy* | –0.0026 | 0.0025 |
| *Number of EFT-POS Terminals per Thousand People* | 0.0005 | –0.0002 |

**Note:** This table reports average marginal effects for the control variables in logit regressions presented in Table 4 (column 3) and Table 5 (column 3).

## Appendix E. Examining the Importance of Historical Cash Usage

In this appendix we attempt to assess the importance of historical cash usage in determining *Cashless Switch* and *Cashless Intention*. Our questionnaire allows us to measure the past use of cash (and by implication cashless instruments), as it includes an item phrased as follows:

**Table E.1. Dummy Variables**

| Variables | | No. of Cases |
|---|---|---|
| CASH_0 | 0% of the Payments Made by Cash | 363 |
| CASH_30 | From 1% to 30% of the Payments Made by Cash | 2,901 |
| CASH_60 | From 31% to 60% of the Payments Made by Cash | 1,217 |
| CASH_99 | From 61% to 99% of the Payments Made by Cash | 575 |
| CASH_100 | 100% of the Payments Made by Cash | 448 |

*What was the share of individual payment methods in your purchases in physical stores and service outlets in the last 12 months?*

*[Please specify the shares in the number of transactions, not the value. The selected answers should add up to approximately 100%.]*

From the responses recorded, we were able to obtain data on intensity of cash utilization, which was divided into five brackets. These were later transformed into dummy variables, as shown in Table E.1.

Subsequently, these dummies were entered into our logit regressions, while simultaneously excluding the *Cards & Mobile* dummy in order to alleviate any multicollinearity concerns. In a similar vein, one of the dummies (CASH_99) is omitted to circumvent the perfect multicollinearity problem. The results are presented in Tables E.2 and E.3.

**Table E.2. Modeling the Switch to Cashless Payments during the Pandemic (including past payment behavior)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1655** | 0.1415* | 0.1477* |
| | (0.0775) | (0.0787) | (0.0790) |
| *Location Size* | 0.0357 | 0.0257 | 0.0284 |
| | (0.0250) | (0.0255) | (0.0257) |
| *Age* | 0.0039 | 0.0056** | 0.0053** |
| | (0.0026) | (0.0027) | (0.0027) |
| *Anonymity* | –0.0226 | –0.0920*** | –0.0808** |
| | (0.0339) | (0.0351) | (0.0352) |

(*continued*)

**Table E.2. (Continued)**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| *Convenience of Cashless Payments* | –0.0116 | –0.0404 | –0.0371 |
| | (0.0543) | (0.0565) | (0.0566) |
| *Safety of Cashless Payments* | 0.0875 | 0.0891 | 0.0816 |
| | (0.0608) | (0.0614) | (0.0622) |
| *Access to Cashless Payments Technologies* | 0.0250 | –0.0393 | –0.0323 |
| | (0.0536) | (0.0555) | (0.0557) |
| *Ease of Use of Cashless Technologies* | 0.1551** | 0.1739*** | 0.1650*** |
| | (0.0614) | (0.0626) | (0.0629) |
| *Control over Finance with Cashless Payments* | 0.0061 | –0.0301 | –0.0329 |
| | (0.0547) | (0.0553) | (0.0561) |
| *Literacy in Using Mobile Apps* | 0.3421*** | 0.3313*** | 0.3312*** |
| | (0.0479) | (0.0480) | (0.0483) |
| *Experience in Using Computer Payments* | 0.0755** | 0.0333 | 0.0374 |
| | (0.0373) | (0.0378) | (0.0380) |
| *Experience in Using Mobile Payments* | 0.0216 | 0.0004 | 0.0041 |
| | (0.0453) | (0.0471) | (0.0466) |
| *COVID Deaths* | 0.0211*** | 0.0145* | 0.0154** |
| | (0.0073) | (0.0076) | (0.0076) |
| *Shadow Economy* | –0.0097* | –0.0154*** | –0.0165*** |
| | (0.0059) | (0.0059) | (0.0060) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0030 | 0.0004 | 0.0012 |
| | (0.0025) | (0.0026) | (0.0026) |
| *Net Fear of Cash* | 0.2615*** | | 0.2232*** |
| | (0.0391) | | (0.0398) |
| *Change in Habits Related to Physical Contact* | | 0.4739*** | 0.4533*** |
| | | (0.0428) | (0.0429) |
| *Change in Online Habits* | | 0.0736* | 0.0753* |
| | | (0.0400) | (0.0401) |
| CASH_0 | 0.6380*** | 0.5973*** | 0.5477*** |
| | (0.1903) | (0.1898) | (0.1938) |
| CASH_30 | 1.0890*** | 1.0979*** | 1.0739*** |
| | (0.1337) | (0.1361) | (0.1370) |
| CASH_60 | 0.8344*** | 0.8203*** | 0.8308*** |
| | (0.1420) | (0.1453) | (0.1463) |
| CASH_100 | –0.1690 | –0.2671 | –0.2335 |
| | (0.1891) | (0.1907) | (0.1920) |
| Constant | –1.3766*** | –0.8782*** | –0.9617*** |
| | (0.2892) | (0.2980) | (0.2993) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 415.1 | 446.6 | 477.4 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.109 | 0.129 | 0.136 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

**Table E.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including past payment behavior)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1780** | 0.1435* | 0.1578* |
| | (0.0804) | (0.0849) | (0.0860) |
| *Location Size* | 0.0322 | 0.0163 | 0.0196 |
| | (0.0253) | (0.0273) | (0.0276) |
| *Age* | 0.0012 | 0.0039 | 0.0032 |
| | (0.0027) | (0.0030) | (0.0030) |
| *Anonymity* | 0.0544 | –0.0916** | –0.0770* |
| | (0.0356) | (0.0395) | (0.0400) |
| *Convenience of Cashless Payments* | 0.0501 | 0.0092 | 0.0129 |
| | (0.0569) | (0.0623) | (0.0631) |
| *Safety of Cashless Payments* | 0.2231*** | 0.2458*** | 0.2436*** |
| | (0.0634) | (0.0699) | (0.0706) |
| *Access to Cashless Payments Technologies* | 0.0469 | –0.0849 | –0.0759 |
| | (0.0563) | (0.0652) | (0.0661) |
| *Ease of Use of Cashless Technologies* | 0.1948*** | 0.2416*** | 0.2252*** |
| | (0.0654) | (0.0725) | (0.0740) |
| *Control over Finance with Cashless Payments* | 0.1198** | 0.0545 | 0.0569 |
| | (0.0565) | (0.0614) | (0.0631) |
| *Literacy in Using Mobile Apps* | 0.1072** | 0.0807 | 0.0740 |
| | (0.0485) | (0.0524) | (0.0532) |
| *Experience in Using Computer Payments* | 0.1193*** | 0.0432 | 0.0507 |
| | (0.0401) | (0.0423) | (0.0432) |
| *Experience in Using Mobile Payments* | 0.0293 | –0.0063 | –0.0005 |
| | (0.0468) | (0.0498) | (0.0499) |
| *COVID Deaths* | 0.0260*** | 0.0152* | 0.0169** |
| | (0.0074) | (0.0078) | (0.0078) |
| *Shadow Economy* | 0.0171*** | 0.0064 | 0.0052 |
| | (0.0061) | (0.0065) | (0.0065) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0005 | –0.0047* | –0.0034 |
| | (0.0027) | (0.0028) | (0.0029) |
| *Net Fear of Cash* | 0.4185*** | | 0.3702*** |
| | (0.0439) | | (0.0473) |
| *Change in Habits Related to Physical Contact* | | 1.0197*** | 0.9985*** |
| | | (0.0552) | (0.0557) |
| *Change in Online Habits* | | 0.0772* | 0.0800* |
| | | (0.0449) | (0.0460) |
| CASH_0 | 1.1021*** | 1.1036*** | 1.0491*** |
| | (0.2043) | (0.2210) | (0.2283) |
| CASH_30 | 1.2600*** | 1.3722*** | 1.3461*** |
| | (0.1492) | (0.1553) | (0.1587) |
| CASH_60 | 0.7843*** | 0.7808*** | 0.7989*** |
| | (0.1574) | (0.1645) | (0.1676) |

(*continued*)

**Table E.3. (Continued)**

| | (1) | (2) | (3) |
|---|---|---|---|
| CASH_100 | 0.1125 | –0.0596 | –0.0039 |
| | (0.2048) | (0.2100) | (0.2132) |
| Constant | –2.4349*** | –1.5902*** | –1.7295*** |
| | (0.3086) | (0.3249) | (0.3299) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 503.1 | 630.1 | 642.3 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.146 | 0.230 | 0.245 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

## Appendix F. Measuring Cashless Payments Attributes Relative to Cash

In the main body of our paper, we have quantified different aspects of cashless payments (convenience, safety, access, ease of use, and control over finance) using factor analysis. This is because we needed to aggregate information on a multitude of payment technologies. The resultant variables were absolute measures, in the sense that they pertained to the cashless technologies alone.

In this appendix we produce regressions where these characteristics are expressed in relative terms. In other words, the attributes of cashless instruments were compared to those of cash. A critical issue that needs to be elucidated here is the procedure that was followed to construct these relative measures. It can be broken into two distinct steps:

(i) For any given payment characteristic (e.g., convenience or safety), we calculate the score differences between each of the six payment instruments (payment cards; HCE payments; Google Pay, Apple Pay, QR, wearables) and cash.

(ii) Factor analysis is then deployed to aggregate the score differences across all payment instruments.

In the regressions that follow (Tables F.1 and F.2), we add the word "Net" in front of a payment characteristic to highlight the fact that it has been calculated relative to cash.

**Table F.1. Modeling the Switch to Cashless Payments during the Pandemic (net constructs)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1776** | 0.1483* | 0.1558** |
| | (0.0765) | (0.0776) | (0.0779) |
| *Location Size* | 0.0287 | 0.0184 | 0.0215 |
| | (0.0250) | (0.0255) | (0.0256) |
| *Age* | 0.0060** | 0.0070*** | 0.0067** |
| | (0.0025) | (0.0026) | (0.0026) |

(*continued*)

**Table F.1. (Continued)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Cards & Mobile* | 0.6598*** | 0.7166*** | 0.7073*** |
| | (0.1310) | (0.1330) | (0.1330) |
| *Anonymity* | –0.0174 | –0.0943*** | –0.0824** |
| | (0.0341) | (0.0352) | (0.0353) |
| *Net Convenience of Cashless Payments* | –0.1688*** | –0.1895*** | –0.1678*** |
| | (0.0512) | (0.0522) | (0.0527) |
| *Net Safety of Cashless Payments* | 0.1660*** | 0.1401** | 0.1375** |
| | (0.0534) | (0.0544) | (0.0549) |
| *Net Access to Cashless Payments Technologies* | –0.0117 | –0.0935* | –0.0736 |
| | (0.0503) | (0.0506) | (0.0514) |
| *Net Ease of Use of Cashless Technologies* | 0.0511 | 0.0448 | 0.0332 |
| | (0.0565) | (0.0574) | (0.0578) |
| *Net Control over Finance with Cashless Payments* | 0.0136 | –0.0047 | –0.0051 |
| | (0.0475) | (0.0484) | (0.0487) |
| *Literacy in Using Mobile Apps* | 0.3682*** | 0.3556*** | 0.3548*** |
| | (0.0468) | (0.0470) | (0.0473) |
| *Experience in Using Computer Payments* | 0.0688* | 0.0249 | 0.0282 |
| | (0.0357) | (0.0365) | (0.0369) |
| *Experience in Using Mobile Payments* | 0.0486 | 0.0204 | 0.0231 |
| | (0.0438) | (0.0454) | (0.0452) |
| *COVID Deaths* | 0.0203*** | 0.0139* | 0.0150** |
| | (0.0072) | (0.0074) | (0.0074) |
| *Shadow Economy* | –0.0156*** | –0.0229*** | –0.0233*** |
| | (0.0058) | (0.0059) | (0.0059) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0033 | 0.0008 | 0.0016 |
| | (0.0025) | (0.0026) | (0.0026) |
| *Net Fear of Cash* | 0.2708*** | | 0.2308*** |
| | (0.0391) | | (0.0399) |
| *Change in Habits Related to Physical Contact* | | 0.4739*** | 0.4520*** |
| | | (0.0421) | (0.0422) |
| *Change in Online Habits* | | 0.0711* | 0.0723* |
| | | (0.0397) | (0.0398) |
| Constant | –1.1584*** | –0.6335** | –0.7352** |
| | (0.2834) | (0.2891) | (0.2913) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 357.5 | 406.0 | 440.7 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.093 | 0.112 | 0.120 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

**Table F.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (net constructs)**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| *Gender* | 0.1922** | 0.1496* | 0.1639* |
| | (0.0789) | (0.0833) | (0.0844) |
| *Location Size* | 0.0299 | 0.0116 | 0.0162 |
| | (0.0252) | (0.0271) | (0.0272) |
| *Age* | 0.0038 | 0.0054* | 0.0047 |
| | (0.0027) | (0.0028) | (0.0029) |
| *Cards & Mobile* | 0.5695*** | 0.7256*** | 0.7111*** |
| | (0.1411) | (0.1425) | (0.1427) |
| *Anonymity* | 0.0727** | –0.0902** | –0.0739* |
| | (0.0353) | (0.0390) | (0.0393) |
| *Net Convenience of Cashless Payments* | –0.3054 | –0.3796 | –0.3457 |
| | (0.0516) | (0.0585) | (0.0589) |
| *Net Safety of Cashless Payments* | 0.1512*** | 0.1051* | 0.1066* |
| | (0.0556) | (0.0604) | (0.0615) |
| *Net Access to Cashless Payments Technologies* | –0.0147 | –0.1826 | –0.1505 |
| | (0.0519) | (0.0562) | (0.0570) |
| *Net Ease of Use of Cashless Technologies* | 0.1127* | 0.1090* | 0.0899 |
| | (0.0582) | (0.0635) | (0.0646) |
| *Net Control over Finance with Cashless Payments* | 0.1176** | 0.0937* | 0.0985* |
| | (0.0482) | (0.0544) | (0.0546) |
| *Literacy in Using Mobile Apps* | 0.1468*** | 0.1207** | 0.1148** |
| | (0.0478) | (0.0511) | (0.0516) |
| *Experience in Using Computer Payments* | 0.1442*** | 0.0639 | 0.0711* |
| | (0.0402) | (0.0408) | (0.0426) |
| *Experience in Using Mobile Payments* | 0.1088** | 0.0628 | 0.0680 |
| | (0.0461) | (0.0473) | (0.0478) |
| *COVID Deaths* | 0.0223*** | 0.0113 | 0.0133* |
| | (0.0074) | (0.0077) | (0.0078) |
| *Shadow Economy* | 0.0076 | –0.0068 | –0.0071 |
| | (0.0059) | (0.0063) | (0.0063) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0010 | –0.0042 | –0.0030 |
| | (0.0026) | (0.0028) | (0.0028) |
| *Net Fear of Cash* | 0.4267*** | | 0.3741*** |
| | (0.0438) | | (0.0478) |
| *Change in Habits Related to Physical Contact* | | 1.0339*** | 1.0110*** |
| | | (0.0555) | (0.0559) |
| *Change in Online Habits* | | 0.0736* | 0.0759* |
| | | (0.0444) | (0.0453) |
| Constant | –1.9791*** | –1.0295*** | –1.1886*** |
| | (0.2908) | (0.3041) | (0.3094) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 412.0 | 544.3 | 553.6 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.119 | 0.207 | 0.223 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

## Appendix G

### Table G.1. Modeling the Switch to Cashless Payments during the Pandemic (age brackets)

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1722** | 0.1488* | 0.1548** |
| | (0.0762) | (0.0773) | (0.0778) |
| *Location Size* | 0.0247 | 0.0139 | 0.0175 |
| | (0.0249) | (0.0253) | (0.0255) |
| *Age* < 30 | –0.0830 | –0.1504 | –0.1187 |
| | (0.1649) | (0.1686) | (0.1692) |
| *Age* >= 30 and < 40 | –0.0949 | –0.2115 | –0.1697 |
| | (0.1653) | (0.1686) | (0.1696) |
| *Age* >= 40 and < 50 | 0.0953 | 0.0413 | 0.0744 |
| | (0.1589) | (0.1624) | (0.1625) |
| *Age* >= 50 and < 60 | –0.0289 | –0.0275 | –0.0141 |
| | (0.1604) | (0.1622) | (0.1634) |
| *Age* >= 60 and < 70 | 0.2033 | 0.0070*** | 0.0067** |
| | (0.1547) | (0.0026) | (0.0026) |
| *Cards & Mobile* | 0.6639*** | 0.7404*** | 0.7244*** |
| | (0.1324) | (0.1339) | (0.1340) |
| *Anonymity* | –0.0563* | –0.1240*** | –0.1094*** |
| | (0.0337) | (0.0348) | (0.0351) |
| *Convenience of Cashless Payments* | 0.0067 | –0.0258 | –0.0215 |
| | (0.0537) | (0.0562) | (0.0564) |
| *Safety of Cashless Payments* | 0.1214** | 0.1257** | 0.1158* |
| | (0.0595) | (0.0601) | (0.0607) |
| *Access to Cashless Payments Technologies* | 0.0228 | –0.0447 | –0.0376 |
| | (0.0535) | (0.0547) | (0.0552) |
| *Ease of Use of Cashless Technologies* | 0.1514** | 0.1698*** | 0.1592*** |
| | (0.0600) | (0.0616) | (0.0616) |
| *Control over Finance with Cashless Payments* | 0.0135 | –0.0176 | –0.0209 |
| | (0.0529) | (0.0538) | (0.0544) |
| *Literacy in Using Mobile Apps* | 0.3771*** | 0.3660*** | 0.3639*** |
| | (0.0466) | (0.0469) | (0.0472) |
| *Experience in Using Computer Payments* | 0.0652* | 0.0200 | 0.0253 |
| | (0.0360) | (0.0369) | (0.0372) |
| *Experience in Using Mobile Payments* | 0.0444 | 0.0209 | 0.0230 |
| | (0.0442) | (0.0460) | (0.0458) |
| *COVID Deaths* | 0.0241*** | 0.0170** | 0.0178** |
| | (0.0072) | (0.0075) | (0.0075) |
| *Shadow Economy* | –0.0139** | –0.0199*** | –0.0209*** |
| | (0.0057) | (0.0058) | (0.0059) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0032 | 0.0003 | 0.0013 |
| | (0.0025) | (0.0026) | (0.0026) |
| *Net Fear of Cash* | 0.2844*** | | 0.2459*** |
| | (0.0390) | | (0.0398) |
| *Change in Habits Related to Physical Contact* | | 0.4777*** | 0.4554*** |
| | | (0.0420) | (0.0421) |

(*continued*)

**Table G.1. (Continued)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Change in Online Habits* | | 0.0952** | 0.0951** |
| | | (0.0394) | (0.0395) |
| Constant | –0.8453*** | –0.2807 | –0.4228 |
| | (0.2801) | (0.2852) | (0.2870) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 350.5 | 401.6 | 440.6 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.0895 | 0.110 | 0.118 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

**Table G.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (age brackets)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1973** | 0.1593* | 0.1745** |
| | (0.0788) | (0.0829) | (0.0843) |
| *Location Size* | 0.0222 | 0.0056 | 0.0103 |
| | (0.0253) | (0.0271) | (0.0273) |
| *Age* < 30 | –0.1573 | –0.2533 | –0.1952 |
| | (0.1663) | (0.1794) | (0.1813) |
| *Age* >= 30 and < 40 | –0.0453 | –0.2357 | –0.1645 |
| | (0.1622) | (0.1748) | (0.1751) |
| *Age* >= 40 and < 50 | –0.2829* | –0.3789** | –0.3258* |
| | (0.1604) | (0.1712) | (0.1720) |
| *Age* >= 50 and < 60 | –0.3640** | –0.3714** | –0.3543** |
| | (0.1621) | (0.1732) | (0.1750) |
| *Age* >= 60 and < 70 | 0.0076 | –0.0150 | 0.0387 |
| | (0.1549) | (0.1651) | (0.1668) |
| *Cards & Mobile* | 0.5699*** | 0.7454*** | 0.7224*** |
| | (0.1433) | (0.1430) | (0.1442) |
| *Anonymity* | 0.0127 | –0.1285*** | –0.1084*** |
| | (0.0348) | (0.0386) | (0.0393) |

(*continued*)

**Table G.2. (Continued)**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| *Convenience of Cashless Payments* | 0.0701 | 0.0264 | 0.0304 |
| | (0.0555) | (0.0615) | (0.0621) |
| *Safety of Cashless Payments* | 0.2607*** | 0.2839*** | 0.2805*** |
| | (0.0633) | (0.0696) | (0.0705) |
| *Access to Cashless Payments Technologies* | 0.0518 | –0.0873 | –0.0788 |
| | (0.0571) | (0.0639) | (0.0652) |
| *Ease of Use of Cashless Technologies* | 0.1919*** | 0.2355*** | 0.2165*** |
| | (0.0636) | (0.0707) | (0.0718) |
| *Control over Finance with Cashless Payments* | 0.1103** | 0.0590 | 0.0598 |
| | (0.0545) | (0.0599) | (0.0615) |
| *Literacy in Using Mobile Apps* | 0.1522*** | 0.1263** | 0.1177** |
| | (0.0470) | (0.0511) | (0.0517) |
| *Experience in Using Computer Payments* | 0.1134*** | 0.0325 | 0.0427 |
| | (0.0392) | (0.0408) | (0.0423) |
| *Experience in Using Mobile Payments* | 0.0615 | 0.0270 | 0.0297 |
| | (0.0460) | (0.0480) | (0.0485) |
| *COVID Deaths* | 0.0286*** | 0.0172** | 0.0190** |
| | (0.0074) | (0.0077) | (0.0078) |
| *Shadow Economy* | 0.0105* | –0.0012 | –0.0022 |
| | (0.0059) | (0.0062) | (0.0063) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0006 | –0.0048* | –0.0034 |
| | (0.0026) | (0.0028) | (0.0028) |
| *Net Fear of Cash* | 0.4448*** | | 0.3981*** |
| | (0.0435) | | (0.0469) |
| *Change in Habits Related to Physical Contact* | | 1.0052*** | 0.9827*** |
| | | (0.0547) | (0.0551) |
| *Change in Online Habits* | | 0.1127** | 0.1150** |
| | | (0.0445) | (0.0456) |
| Constant | –1.5871*** | –0.6104** | –0.8494*** |
| | (0.2807) | (0.2987) | (0.3026) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 407.0 | 534.6 | 552.7 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.125 | 0.206 | 0.225 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

## Appendix H

### Table H.1. Modeling the Switch to Cashless Payments during the Pandemic (cash users only)

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1543* | 0.1290 | 0.1361* |
| | (0.0787) | (0.0797) | (0.0802) |
| *Location Size* | 0.0217 | 0.0099 | 0.0150 |
| | (0.0257) | (0.0262) | (0.0263) |
| *Age* | 0.0041 | 0.0061** | 0.0056** |
| | (0.0026) | (0.0027) | (0.0027) |
| *Cards & Mobile* | 0.6548*** | 0.7256*** | 0.7133*** |
| | (0.1359) | (0.1367) | (0.1370) |
| *Anonymity* | –0.0832** | –0.1440*** | –0.1301*** |
| | (0.0349) | (0.0358) | (0.0361) |
| *Convenience of Cashless Payments* | 0.0052 | –0.0295 | –0.0231 |
| | (0.0552) | (0.0576) | (0.0578) |
| *Safety of Cashless Payments* | 0.0803 | 0.0953 | 0.0773 |
| | (0.0618) | (0.0628) | (0.0631) |
| *Access to Cashless Payments Technologies* | 0.0286 | –0.0338 | –0.0287 |
| | (0.0554) | (0.0566) | (0.0570) |
| *Ease of Use of Cashless Technologies* | 0.1697*** | 0.1865*** | 0.1780*** |
| | (0.0626) | (0.0640) | (0.0641) |
| *Control over Finance with Cashless Payments* | 0.0215 | –0.0125 | –0.0136 |
| | (0.0552) | (0.0560) | (0.0567) |
| *Literacy in Using Mobile Apps* | 0.3890*** | 0.3802*** | 0.3763*** |
| | (0.0489) | (0.0490) | (0.0493) |
| *Experience in Using Computer Payments* | 0.0469 | –0.0013 | 0.0029 |
| | (0.0369) | (0.0372) | (0.0377) |
| *Experience in Using Mobile Payments* | 0.0371 | 0.0133 | 0.0156 |
| | (0.0452) | (0.0466) | (0.0465) |
| *COVID Deaths* | 0.0258*** | 0.0191** | 0.0198*** |
| | (0.0073) | (0.0076) | (0.0076) |
| *Shadow Economy* | –0.0131** | –0.0191*** | –0.0200*** |
| | (0.0058) | (0.0059) | (0.0060) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0024 | –0.0004 | 0.0006 |
| | (0.0025) | (0.0026) | (0.0026) |
| *Net Fear of Cash* | 0.2936*** | | 0.2605*** |
| | (0.0408) | | (0.0419) |
| *Change in Habits Related to Physical Contact* | | 0.4597*** | 0.4385*** |
| | | (0.0437) | (0.0438) |
| *Change in Online Habits* | | 0.0959** | 0.0980** |
| | | (0.0404) | (0.0406) |
| Constant | –0.9015*** | –0.4926* | –0.5932** |
| | (0.2915) | (0.2969) | (0.2995) |
| Observations | 5,141 | 5,141 | 5,141 |
| chi2 | 323.1 | 362.8 | 398.1 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.089 | 0.106 | 0.115 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

**Table H.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (cash users only)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1886** | 0.1461* | 0.1627* |
| | (0.0814) | (0.0860) | (0.0873) |
| *Location Size* | 0.0212 | 0.0028 | 0.0089 |
| | (0.0263) | (0.0281) | (0.0285) |
| *Age* | 0.0026 | 0.0059** | 0.0050 |
| | (0.0027) | (0.0030) | (0.0030) |
| *Cards & Mobile* | 0.5979*** | 0.7745*** | 0.7606*** |
| | (0.1477) | (0.1442) | (0.1459) |
| *Anonymity* | –0.0159 | –0.1526*** | –0.1351*** |
| | (0.0360) | (0.0397) | (0.0404) |
| *Convenience of Cashless Payments* | 0.0629 | 0.0128 | 0.0198 |
| | (0.0578) | (0.0638) | (0.0647) |
| *Safety of Cashless Payments* | 0.2651*** | 0.3123*** | 0.2968*** |
| | (0.0666) | (0.0732) | (0.0741) |
| *Access to Cashless Payments Technologies* | 0.0757 | –0.0550 | –0.0488 |
| | (0.0591) | (0.0666) | (0.0682) |
| *Ease of Use of Cashless Technologies* | 0.2033*** | 0.2441*** | 0.2294*** |
| | (0.0663) | (0.0736) | (0.0750) |
| *Control over Finance with Cashless Payments* | 0.1091* | 0.0468 | 0.0524 |
| | (0.0569) | (0.0621) | (0.0641) |
| *Literacy in Using Mobile Apps* | 0.1412*** | 0.1168** | 0.1053** |
| | (0.0489) | (0.0530) | (0.0536) |
| *Experience in Using Computer Payments* | 0.1101*** | 0.0204 | 0.0287 |
| | (0.0404) | (0.0416) | (0.0436) |
| *Experience in Using Mobile Payments* | 0.0668 | 0.0326 | 0.0358 |
| | (0.0472) | (0.0494) | (0.0500) |
| *COVID Deaths* | 0.0279*** | 0.0166** | 0.0181** |
| | (0.0075) | (0.0079) | (0.0079) |
| *Shadow Economy* | 0.0087 | –0.0037 | –0.0046 |
| | (0.0061) | (0.0064) | (0.0065) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0008 | –0.0046 | –0.0031 |
| | (0.0026) | (0.0028) | (0.0028) |
| *Net Fear of Cash* | 0.4474*** | | 0.4104*** |
| | (0.0460) | | (0.0492) |
| *Change in Habits Related to Physical Contact* | | 1.0185*** | 1.0005*** |
| | | (0.0570) | (0.0577) |
| *Change in Online Habits* | | 0.1126** | 0.1181** |
| | | (0.0458) | (0.0473) |
| Constant | –1.7559*** | –1.0091*** | –1.1621*** |
| | (0.3007) | (0.3152) | (0.3202) |
| Observations | 5,141 | 5,141 | 5,141 |
| chi2 | 382.7 | 531.8 | 539.0 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.125 | 0.208 | 0.227 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

## Appendix I. Moderating Effects

In this appendix we investigate whether interaction models could inform us about country-level factors that moderate the relationship between the COVID pandemic and the willingness to switch to cashless payments. Eight different variables are considered as possible moderating factors, which are subsequently interacted in our logistic regressions with *Net Fear of Cash* and the two changes in habits variables. To ease the task of interpretation and alleviate multicollinearity concerns, these eight variables are constructed as dummies that partition our sample into two groups—one in which a given characteristic exists or is prominent (i.e., records an above-median value) and one in which it is not. Three binary indicators were constructed from variables already used in our main analysis, namely *COVID Deaths, Shadow Economy*, and *Number of EFT-POS Terminals per Thousand People*, whereas two additional dummies derive from country scores for power distance and uncertainty avoidance index retrieved from the Hofstede national culture data set. Another two dichotomous variables split the sample into Scandinavian and non-Scandinavian countries, as well as developed versus emerging economies based on the value of GDP per capita in 2020 measured at purchasing power parity prices. The GDP data were sourced from the World Development Indicators database maintained by the World Bank. Finally, we split the countries according to their COVID stringency index, which measures the severity of policy responses to COVID-19 pandemic and was compiled by Mathieu et al. (2020). The values of the stringency index were averaged during the July to August 2020 period, which covers the timeframe when the survey was conducted. Table I.1 catalogues and describes the interaction dummies.

Table I.2 presents logit regressions with interaction terms that model the decision to pay cashless more often during the COVID pandemic.

As there are as many as 24 interaction terms across the eight regressions in the table above, we restrict ourselves to analyzing only those that are statistically significant at the 5 percent level or better. Firstly, the interaction between the Scandinavian country dummy and *Net Fear of Cash* bears a negative coefficient and proves meaningful to the choice of cashless payments during the COVID

**Table I.1. Definitions of Variables**

| Variable | Definition |
|---|---|
| *D_Scand* | A dummy variable taking a value of one if the respondent resides in a Scandinavian country and zero otherwise |
| *D_Deaths* | A dummy variable taking a value of one if the respondent is from a country with an above-median number of COVID-19 deaths and zero otherwise |
| *D_Shadow* | A dummy variable taking a value of one if the respondent's country has an above-median size of the shadow economy (as a percentage of GDP) and zero otherwise |
| *D_Stringency* | A dummy variable taking a value of one if the respondent resides in a country with an above-median value of the COVID stringency index and zero otherwise |
| *D_Developed* | A dummy variable taking a value of one if the respondent inhabits a country with an above-median value of GDP per capita in international dollars in 2020 and zero otherwise |
| *D_PD* | A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede power distance indicator and zero otherwise |
| *D_UA* | A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede uncertainty avoidance index and zero otherwise |
| *D_Terminals* | A dummy variable taking a value of one if the respondent's country has an above-median number of EFT-POS terminals per thousand people and zero otherwise |

epidemic. As is shown in Appendix B, respondents in all of the Scandinavian countries in our sample (Denmark, Finland, Norway, Sweden) showed below-average tendency to change their habits in response to infection risk. Similarly, many of them failed to act out their fears through switching from cash to payment instruments offering a lower risk of virus transmission. Scandinavia had already been characterized by a very high level of electronic payments prior to the COVID outbreak (Armelius, Claussen, and Reslow 2022; Engert, Fung, and Segendorf 2020), which limited the scope of further abandonment of physical currency for transactional purposes. Secondly, the impact of changes in habits in the physical space is lessened for countries with high values of the COVID stringency index. In such countries, changes in behavior may have been primarily driven by the regulations rather than the free will of respondents. Switch to cashless payments, which is entirely voluntary in

**Table I.2. Modeling the Switch to Cashless Payments during the Pandemic (including interaction terms)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Gender* | 0.1616** | 0.1627** | 0.1536** | 0.1642** | 0.1585** | 0.1636** | 0.1563** | 0.1558** |
| | (0.0779) | (0.0779) | (0.0778) | (0.0779) | (0.0779) | (0.0779) | (0.0779) | (0.0778) |
| *Location Size* | 0.0189 | 0.0194 | 0.0185 | 0.0200 | 0.0202 | 0.0193 | 0.0185 | 0.0190 |
| | (0.0255) | (0.0255) | (0.0255) | (0.0254) | (0.0255) | (0.0254) | (0.0255) | (0.0256) |
| *Age* | 0.0063** | 0.0063** | 0.0063** | 0.0062** | 0.0062** | 0.0061** | 0.0063** | 0.0065** |
| | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| *Cards & Mobile* | 0.7320*** | 0.7251*** | 0.7337*** | 0.7256*** | 0.7240*** | 0.7295*** | 0.7311*** | 0.7360*** |
| | (0.1337) | (0.1332) | (0.1338) | (0.1332) | (0.1337) | (0.1332) | (0.1340) | (0.1338) |
| *Anonymity* | –0.1082*** | –0.1066*** | –0.1084*** | –0.1061*** | –0.1084*** | –0.1068*** | –0.1100*** | –0.1060*** |
| | (0.0349) | (0.0348) | (0.0348) | (0.0348) | (0.0349) | (0.0348) | (0.0349) | (0.0348) |
| *Convenience of Cashless Payments* | –0.0214 | –0.0218 | –0.0236 | –0.0198 | –0.0246 | –0.0197 | –0.0236 | –0.0244 |
| | (0.0560) | (0.0560) | (0.0560) | (0.0559) | (0.0561) | (0.0559) | (0.0560) | (0.0560) |
| *Safety of Cashless Payments* | 0.1133* | 0.1174* | 0.1152* | 0.1190** | 0.1135* | 0.1205** | 0.1115* | 0.1155* |
| | (0.0605) | (0.0605) | (0.0605) | (0.0607) | (0.0605) | (0.0609) | (0.0604) | (0.0607) |
| *Access to Cashless Payments Technologies* | –0.0348 | –0.0374 | –0.0362 | –0.0358 | –0.0364 | –0.0377 | –0.0302 | –0.0356 |
| | (0.0553) | (0.0551) | (0.0551) | (0.0551) | (0.0552) | (0.0551) | (0.0553) | (0.0551) |
| *Ease of Use of Cashless Technologies* | 0.1581** | 0.1587** | 0.1560** | 0.1572** | 0.1616*** | 0.1573** | 0.1602*** | 0.1529** |
| | (0.0618) | (0.0618) | (0.0618) | (0.0618) | (0.0618) | (0.0618) | (0.0618) | (0.0617) |
| *Control over Finance with Cashless Payments* | –0.0247 | –0.0219 | –0.0213 | –0.0208 | –0.0244 | –0.0204 | –0.0254 | –0.0201 |
| | (0.0544) | (0.0544) | (0.0544) | (0.0544) | (0.0545) | (0.0544) | (0.0546) | (0.0545) |
| *Literacy in Using Mobile Apps* | 0.3641*** | 0.3624*** | 0.3635*** | 0.3639*** | 0.3637*** | 0.3632*** | 0.3638*** | 0.3641*** |
| | (0.0473) | (0.0473) | (0.0472) | (0.0474) | (0.0472) | (0.0474) | (0.0471) | (0.0472) |
| *Experience in Using Computer Payments* | 0.0219 | 0.0195 | 0.0206 | 0.0206 | 0.0231 | 0.0224 | 0.0201 | 0.0213 |
| | (0.0373) | (0.0372) | (0.0373) | (0.0373) | (0.0373) | (0.0372) | (0.0373) | (0.0371) |
| *Experience in Using Mobile Payments* | 0.0185 | 0.0198 | 0.0164 | 0.0196 | 0.0181 | 0.0192 | 0.0189 | 0.0207 |
| | (0.0458) | (0.0459) | (0.0459) | (0.0460) | (0.0460) | (0.0460) | (0.0457) | (0.0459) |
| *COVID Deaths* | 0.0180** | 0.0191** | 0.0181** | 0.0181** | 0.0191** | 0.0176** | 0.0186** | 0.0169** |
| | (0.0075) | (0.0075) | (0.0075) | (0.0075) | (0.0075) | (0.0076) | (0.0075) | (0.0075) |
| *Shadow Economy* | –0.0202*** | –0.0201*** | –0.0195*** | –0.0202*** | –0.0210*** | –0.0217*** | –0.0201*** | –0.0203*** |
| | (0.0059) | (0.0058) | (0.0060) | (0.0058) | (0.0059) | (0.0060) | (0.0060) | (0.0059) |

(*continued*)

## Table I.2. (Continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Number of EFT-POS Terminals per Thousand People* | 0.0011 | 0.0012 | 0.0012 | 0.0014 | 0.0012 | 0.0019 | 0.0013 | 0.0022 |
| | (0.0026) | (0.0026) | (0.0026) | (0.0025) | (0.0026) | (0.0026) | (0.0026) | (0.0025) |
| *Net Fear of Cash* | 0.2598*** | 0.2740*** | 0.2389*** | 0.2252*** | 0.2179*** | 0.2343*** | 0.1837** | 0.2554*** |
| | (0.0430) | (0.0466) | (0.0500) | (0.0521) | (0.0437) | (0.0567) | (0.0759) | (0.0428) |
| *Change in Habits Related to Physical Contact* | 0.4489*** | 0.4283*** | 0.4889*** | 0.5459*** | 0.4407*** | 0.3894*** | 0.5221*** | 0.4971*** |
| | (0.0441) | (0.0498) | (0.0531) | (0.0580) | (0.0454) | (0.0600) | (0.0922) | (0.0464) |
| *Change in Online Habits* | 0.0977** | 0.0798* | 0.0745 | 0.1323** | 0.1022** | 0.0389* | 0.1471* | 0.0952** |
| | (0.0414) | (0.0457) | (0.0474) | (0.0549) | (0.0424) | (0.0337) | (0.0814) | (0.0423) |
| *Net Fear of Cash × D_Scand* | –0.2067** | | | | | | | |
| | (0.0857) | | | | | | | |
| *Change in Habits Related to Physical Contact × D_Scand* | 0.0604 | | | | | | | |
| | (0.1037) | | | | | | | |
| *Change in Online Habits × D_Scand* | –0.0017 | | | | | | | |
| | (0.0849) | | | | | | | |
| *Net Fear of Cash × D_Deaths* | | –0.1187 | | | | | | |
| | | (0.0892) | | | | | | |
| *Change in Habits Related to Physical Contact × D_Deaths* | | 0.0777 | | | | | | |
| | | (0.0903) | | | | | | |
| *Change in Online Habits × D_Deaths* | | 0.0626 | | | | | | |
| | | (0.0816) | | | | | | |
| *Net Fear of Cash × D_Shadow* | | | 0.0230 | | | | | |
| | | | (0.0780) | | | | | |
| *Change in Habits Related to Physical Contact × D_Shadow* | | | –0.1201 | | | | | |
| | | | (0.0826) | | | | | |
| *Change in Online Habits × D_Shadow* | | | 0.0953 | | | | | |
| | | | (0.0758) | | | | | |
| *Net Fear of Cash × D_Stringency* | | | | 0.0343 | | | | |
| | | | | (0.0749) | | | | |
| *Change in Habits Related to Physical* Contact × *D_Stringency* | | | | –0.1584** | | | | |
| | | | | (0.0805) | | | | |
| *Change in Online Habits × D_Stringency* | | | | –0.0609 | | | | |
| | | | | (0.0735) | | | | |
| *Net Fear of Cash × D_Developed* | | | | | 0.2248*** | | | |
| | | | | | (0.0726) | | | |
| *Change in Habits Related to Physical Contact × D_Developed* | | | | | 0.1565* | | | |
| | | | | | (0.0840) | | | |
| *Change in Online Habits × D_Developed* | | | | | –0.0293 | | | |
| | | | | | (0.0740) | | | |
| *Net Fear of Cash × D_PD* | | | | | | 0.0247 | | |
| | | | | | | (0.0762) | | |

*(continued)*

## Table I.2. (Continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Change in Habits Related to Physical Contact × D_PD* | | | | | | 0.1432* | | |
| | | | | | | (0.0816) | | |
| *Change in Online Habits × D_PD* | | | | | | 0.1311* | | |
| | | | | | | (0.0739) | | |
| *Net Fear of Cash × D_UA* | | | | | | | 0.0838 | |
| | | | | | | | (0.0884) | |
| *Change in Habits Related to Physical Contact × D_UA* | | | | | | | –0.0903 | |
| | | | | | | | (0.1028) | |
| *Change in Online Habits × D_UA* | | | | | | | –0.0616 | |
| | | | | | | | (0.0904) | |
| *Net Fear of Cash × D_Terminals* | | | | | | | | –0.0869 |
| | | | | | | | | (0.1200) |
| *Change in Habits Related to Physical Contact × D_Terminals* | | | | | | | | –0.2770*** |
| | | | | | | | | (0.1075) |
| *Change in Online Habits × D_Terminals* | | | | | | | | 0.0239 |
| | | | | | | | | (0.1062) |
| Constant | –0.7413** | –0.7634*** | –0.7542*** | –0.7552*** | –0.7347** | –0.7368** | –0.7486** | –0.7822*** |
| | (0.2911) | (0.2902) | (0.2917) | (0.2903) | (0.2908) | (0.2917) | (0.2917) | (0.2911) |
| Observations | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 |
| chi2 | 445.9 | 431.3 | 434.2 | 446.5 | 514.9 | 448.2 | 434.8 | 430.6 |
| p | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| r2_p | 0.117 | 0.117 | 0.117 | 0.118 | 0.118 | 0.118 | 0.117 | 0.118 |

**Note:** This table reports egression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

nature, did not seem to keep up with the regulation-induced behavioral shifts. Thirdly, the variable *Net Fear of Cash* exerted a more prominent impact on decision to abandon cash in countries with high GDP per capita. This is unsurprising since the volume of transactions is expected to be higher for respondents from affluent nations. As more cash transactions are made, the risks are swiftly compounding, and the desire to drift away from cash becomes stronger. This, in turn, explains the statistical significance of the interaction variable. Lastly, the impact of *Change in Habits Related to Physical Contact* on the decision to switch to digital payments is weaker in countries with a large number of EFT-POS terminals per capita.

Table I.3 presents models which include interactive terms and in which the intention to increase the frequency of cashless payments after the pandemic is over acts as a dependent variable.

Two of the interactions in Table I.3 appear to be significant at the 5 percent level. Firstly, the impact of changes in habits in the physical sphere on the declared future intention is stronger in societies with a high power distance. Power distance, as the degree to which hierarchical order is accepted within society, could affect trust in institutions and, consequently, in cashless technologies. If a person feels no resistance towards power distance and is prepared to change their physical habits, transition towards cashless payments will loom large on their agenda due to the relatively high trust in financial institutions. Such rationalization is consistent with the observed positive coefficient on the interaction term. Secondly, the societal uncertainty avoidance also appears to magnify the impact of *Change in Habits Related to Physical Contact* on the future intention to transact more cashless. This means that respondents who were willing to change their physical behavior in response to the dangers posed by COVID and resided in uncertainty-averse nations were particularly eager to abandon cash for transactional purposes.

**Table I.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including interaction terms)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Gender* | 0.1768** | 0.1821** | 0.1772** | 0.1820** | 0.1765** | 0.1856** | 0.1809** | 0.1729** |
| | (0.0843) | (0.0842) | (0.0843) | (0.0842) | (0.0844) | (0.0842) | (0.0844) | (0.0842) |
| *Location Size* | 0.0133 | 0.0131 | 0.0134 | 0.0138 | 0.0133 | 0.0131 | 0.0136 | 0.0129 |
| | (0.0272) | (0.0272) | (0.0273) | (0.0272) | (0.0273) | (0.0272) | (0.0272) | (0.0273) |
| *Age* | 0.0046 | 0.0047 | 0.0048 | 0.0046 | 0.0047 | 0.0045 | 0.0044 | 0.0047 |
| | (0.0029) | (0.0029) | (0.0029) | (0.0029) | (0.0029) | (0.0029) | (0.0029) | (0.0029) |
| *Cards & Mobile* | 0.7325*** | 0.7322*** | 0.7336*** | 0.7257*** | 0.7298*** | 0.7340*** | 0.7398*** | 0.7378*** |
| | (0.1440) | (0.1440) | (0.1440) | (0.1436) | (0.1439) | (0.1440) | (0.1452) | (0.1443) |
| *Anonymity* | –0.1124*** | –0.1094*** | –0.1127*** | –0.1107*** | –0.1132*** | –0.1085*** | –0.1108*** | –0.1113*** |
| | (0.0391) | (0.0390) | (0.00391) | (0.0391) | (0.0391) | (0.0391) | (0.0391) | (0.0389) |
| *Convenience of Cashless Payments* | 0.0290 | 0.0297 | 0.0272 | 0.0311 | 0.0269 | 0.0335 | 0.0346 | 0.0260 |
| | (0.0620) | (0.0622) | (0.0620) | (0.0621) | (0.0621) | (0.0621) | (0.0622) | (0.0620) |
| *Safety of Cashless Payments* | 0.2709*** | 0.2758*** | 0.2725*** | 0.2743*** | 0.2716*** | 0.2747*** | 0.2715*** | 0.2730*** |
| | (0.0700) | (0.0701) | (0.0702) | (0.0699) | (0.0701) | (0.0701) | (0.0695) | (0.0701) |
| *Access to Cashless Payments Technologies* | –0.0788 | –0.0777 | –0.0778 | –0.0757 | –0.0795 | –0.0768 | –0.0776 | –0.0785 |
| | (0.0652) | (0.0650) | (0.0651) | (0.0650) | (0.0652) | (0.0650) | (0.0653) | (0.0651) |
| *Ease of Use of Cashless Technologies* | 0.2135*** | 0.2118*** | 0.2122*** | 0.2127*** | 0.2144*** | 0.2121*** | 0.2166*** | 0.2085*** |
| | (0.0718) | (0.0719) | (0.0718) | (0.0717) | (0.0718) | (0.0717) | (0.0718) | (0.0716) |
| *Control over Finance with Cashless Payments* | 0.0711 | 0.0768 | 0.0712 | 0.0740 | 0.0715 | 0.0761 | 0.0682 | 0.0739 |
| | (0.0609) | (0.0608) | (0.0608) | (0.0607) | (0.0609) | (0.0607) | (0.0606) | (0.0608) |
| *Literacy in Using Mobile Apps* | 0.1197** | 0.1197** | 0.1194** | 0.1210** | 0.1196** | 0.1209** | 0.1166** | 0.1202** |
| | (0.0515) | (0.0516) | (0.0514) | (0.0516) | (0.0514) | (0.0516) | (0.0513) | (0.0515) |
| *Experience in Using Computer Payments* | 0.0469 | 0.0440 | 0.0463 | 0.0448 | 0.0471 | 0.0456 | 0.0505 | 0.0467 |
| | (0.0427) | (0.0427) | (0.0426) | (0.0426) | (0.0426) | (0.0424) | (0.0427) | (0.0426) |
| *Experience in Using Mobile Payments* | 0.0345 | 0.0326 | 0.0364 | 0.0336 | 0.0349 | 0.0340 | 0.0393 | 0.0359 |
| | (0.0485) | (0.0488) | (0.0485) | (0.0488) | (0.0486) | (0.0489) | (0.0485) | (0.0487) |
| *COVID Deaths* | 0.0185** | 0.0177** | 0.0183** | 0.0177** | 0.0190** | 0.0163** | 0.0184** | 0.0171** |
| | (0.0078) | (0.0081) | (0.0078) | (0.0078) | (0.0078) | (0.0080) | (0.0078) | (0.0078) |
| *Shadow Economy* | –0.0022 | –0.0019 | –0.0014 | –0.0018 | –0.0026 | –0.0039 | –0.0026 | –0.0018 |
| | (0.0063) | (0.0063) | (0.0066) | (0.0063) | (0.0063) | (0.0065) | (0.0065) | (0.0063) |
| *Number of EFT-POS Terminals per Thousand People* | –0.0036 | –0.0034 | –0.0035 | –0.0034 | –0.0036 | –0.0027 | –0.0036 | –0.0020 |
| | (0.0028) | (0.0028) | (0.0028) | (0.0028) | (0.0028) | (0.0028) | (0.0028) | (0.0028) |
| *Net Fear of Cash* | 0.4024*** | 0.4252*** | 0.3958*** | 0.3473*** | 0.3791*** | 0.4081*** | 0.4475*** | 0.4111*** |
| | (0.0509) | (0.0552) | (0.0597) | (0.0591) | (0.0523) | (0.0691) | (0.0894) | (0.0505) |

(*continued*)

## Table I.3. (Continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Change in Habits Related to Physical Contact* | 0.9850*** | 0.9207*** | 1.0027*** | 1.0920*** | 0.9892*** | 0.8713*** | 0.7927*** | 1.0271*** |
| | (0.0579) | (0.0639) | (0.0697) | (0.0722) | (0.0600) | (0.0771) | (0.1125) | (0.0609) |
| *Change in Online Habits* | 0.1147** | 0.1100** | 0.1205** | 0.0797 | 0.1145** | 0.1309** | 0.2220** | 0.1049** |
| | (0.0475) | (0.0519) | (0.0548) | (0.0618) | (0.0489) | (0.0619) | (0.0917) | (0.0485) |
| *Net Fear of Cash × D_Scand* | –0.0902 | | | | | | | |
| | (0.0926) | | | | | | | |
| *Change in Habits Related to Physical Contact × D_Scand* | –0.0089 | | | | | | | |
| | (0.1250) | | | | | | | |
| *Change in Online Habits × D_Scand* | –0.0875 | | | | | | | |
| | (0.0965) | | | | | | | |
| *Net Fear of Cash × D_Deaths* | | –0.1036 | | | | | | |
| | | (0.1037) | | | | | | |
| *Change in Habits Related to Physical Contact × D_Deaths* | | 0.2193* | | | | | | |
| | | (0.1164) | | | | | | |
| *Change in Online Habits × D_Deaths* | | –0.0008 | | | | | | |
| | | (0.0929) | | | | | | |
| *Net Fear of Cash × D_Shadow* | | | –0.0005 | | | | | |
| | | | (0.0918) | | | | | |
| *Change in Habits Related to Physical Contact × D_Shadow* | | | –0.0622 | | | | | |
| | | | (0.1067) | | | | | |
| *Change in Online Habits × D_Shadow* | | | –0.0404 | | | | | |
| | | | (0.0861) | | | | | |
| *Net Fear of Cash × D_Stringency* | | | | 0.0876 | | | | |
| | | | | (0.0880) | | | | |
| *Change in Habits Related to Physical Contact × D_Stringency* | | | | –0.1827* | | | | |
| | | | | (0.1007) | | | | |
| *Change in Online Habits × D_Stringency* | | | | 0.0501 | | | | |
| | | | | (0.0831) | | | | |
| *Net Fear of Cash × D_Developed* | | | | | 0.1346* | | | |
| | | | | | (0.0815) | | | |
| *Change in Habits Related to Physical Contact × D_Developed* | | | | | –0.0330 | | | |
| | | | | | (0.0996) | | | |
| *Change in Online Habits × D_Developed* | | | | | –0.0442 | | | |
| | | | | | (0.0823) | | | |
| *Net Fear of Cash × D_PD* | | | | | | –0.0228 | | |
| | | | | | | (0.0898) | | |

*(continued)*

## Table I.3. (Continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Change in Habits Related to Physical Contact × D_PD* | | | | | | 0.2526** | | |
| | | | | | | (0.1036) | | |
| *Change in Online Habits × D_PD* | | | | | | –0.0494 | | |
| | | | | | | (0.0834) | | |
| *Net Fear of Cash × D_UA* | | | | | | | –0.0760 | |
| | | | | | | | (0.1038) | |
| *Change in Habits Related to Physical Contact × D_UA* | | | | | | | 0.2548** | |
| | | | | | | | (0.1278) | |
| *Change in Online Habits × D_UA* | | | | | | | –0.1479 | |
| | | | | | | | (0.1022) | |
| *Net Fear of Cash × D_Terminals* | | | | | | | | –0.1018 |
| | | | | | | | | (0.1404) |
| *Change in Habits Related to Physical Contact × D_Terminals* | | | | | | | | –0.2499* |
| | | | | | | | | (0.1340) |
| *Change in Online Habits × D_Terminals* | | | | | | | | 0.0289 |
| | | | | | | | | (0.1226) |
| Constant | –1.2376*** | –1.2580*** | –1.2612*** | –1.2472*** | –1.2340*** | –1.2292*** | –1.2389*** | –1.2904*** |
| | (0.3119) | (0.3112) | (0.3142) | (0.3113) | (0.3115) | (0.3137) | (0.3132) | (0.3123) |
| Observations | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 | 5,504 |
| chi2 | 597.5 | 563.9 | 567.9 | 608.9 | 663.7 | 616.1 | 561.1 | 546.2 |
| p | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| r2_p | 0.223 | 0.224 | 0.223 | 0.224 | 0.223 | 0.225 | 0.225 | 0.224 |

**Note:** This table reports egression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

## Appendix J

### Table J.1. Modeling the Switch to Cashless Payments during the Pandemic (probit estimates)

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1054** | 0.0906* | 0.0952** |
| | (0.0465) | (0.0470) | (0.0472) |
| *Location Size* | 0.0164 | 0.0091 | 0.0111 |
| | (0.0151) | (0.0153) | (0.0154) |
| *Age* | 0.0029* | 0.0039** | 0.0038** |
| | (0.0015) | (0.0016) | (0.0016) |
| *Cards & Mobile* | 0.4067*** | 0.4529*** | 0.4450*** |
| | (0.0782) | (0.0789) | (0.0788) |
| *Anonymity* | –0.0346* | –0.0760*** | –0.0671*** |
| | (0.0205) | (0.0210) | (0.0211) |
| *Convenience of Cashless* | 0.0043 | –0.0169 | –0.0140 |
| *Payments* | (0.0328) | (0.0339) | (0.0339) |
| *Safety of Cashless Payments* | 0.0719** | 0.0748** | 0.0678* |
| | (0.0363) | (0.0364) | (0.0366) |
| *Access to Cashless Payments* | 0.0138 | –0.0234 | –0.0201 |
| *Technologies* | (0.0326) | (0.0332) | (0.0334) |
| *Ease of Use of Cashless* | 0.0933** | 0.1008*** | 0.0953** |
| *Technologies* | (0.0367) | (0.0373) | (0.0374) |
| *Control over Finance with* | 0.0078 | –0.0117 | –0.0134 |
| *Cashless Payments* | (0.0324) | (0.0328) | (0.0331) |
| *Literacy in Using Mobile Apps* | 0.2323*** | 0.2248*** | 0.2233*** |
| | (0.0285) | (0.0286) | (0.0287) |
| *Experience in Using Computer* | 0.0397* | 0.0110 | 0.0140 |
| *Payments* | (0.0219) | (0.0220) | (0.0222) |
| *Experience in Using Mobile* | 0.0253 | 0.0082 | 0.0101 |
| *Payments* | (0.0271) | (0.0280) | (0.0278) |
| *COVID Deaths* | 0.0150*** | 0.0108** | 0.0112** |
| | (0.0044) | (0.0045) | (0.0045) |
| *Shadow Economy* | –0.0081** | –0.0117*** | –0.0122*** |
| | (0.0035) | (0.0035) | (0.0035) |
| *Number of EFT-POS Terminals* | 0.0019 | 0.0001 | 0.0006 |
| *per Thousand People* | (0.0015) | (0.0015) | (0.0016) |
| *Net Fear of Cash* | 0.1718*** | | 0.1495*** |
| | (0.0233) | | (0.0237) |
| *Change in Habits Related to* | | 0.2877*** | 0.2749*** |
| *Physical Contact* | | (0.0249) | (0.0250) |
| *Change in Online Habits* | | 0.0599** | 0.0601** |
| | | (0.0239) | (0.0240) |
| Constant | –0.6550*** | –0.3842** | –0.4484** |
| | (0.1705) | (0.1742) | (0.1748) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 374.5 | 433.7 | 479.1 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.0887 | 0.109 | 0.117 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

**Table J.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (probit estimates)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *Gender* | 0.1136** | 0.0895* | 0.0966* |
| | (0.0475) | (0.0495) | (0.0501) |
| *Location Size* | 0.0164 | 0.0040 | 0.0072 |
| | (0.0153) | (0.0161) | (0.0162) |
| *Age* | 0.0015 | 0.0030* | 0.0025 |
| | (0.0016) | (0.0017) | (0.0017) |
| *Cards & Mobile* | 0.3277*** | 0.4430*** | 0.4256*** |
| | (0.0831) | (0.0845) | (0.0847) |
| *Anonymity* | 0.0059 | –0.0789*** | –0.0680*** |
| | (0.0210) | (0.0227) | (0.0230) |
| *Convenience of Cashless Payments* | 0.0405 | 0.0145 | 0.0151 |
| | (0.0336) | (0.0360) | (0.0364) |
| *Safety of Cashless Payments* | 0.1437*** | 0.1588*** | 0.1520*** |
| | (0.0375) | (0.0405) | (0.0407) |
| *Access to Cashless Payments Technologies* | 0.0306 | –0.0457 | –0.0384 |
| | (0.0339) | (0.0373) | (0.0379) |
| *Ease of Use of Cashless Technologies* | 0.1110*** | 0.1365*** | 0.1277*** |
| | (0.0382) | (0.0413) | (0.0418) |
| *Control over Finance with Cashless Payments* | 0.0729** | 0.0353 | 0.0341 |
| | (0.0329) | (0.0354) | (0.0360) |
| *Literacy in Using Mobile Apps* | 0.0958*** | 0.0797*** | 0.0757*** |
| | (0.0286) | (0.0302) | (0.0305) |
| *Experience in Using Computer Payments* | 0.0737*** | 0.0225 | 0.0290 |
| | (0.0233) | (0.0240) | (0.0245) |
| *Experience in Using Mobile Payments* | 0.0444 | 0.0193 | 0.0224 |
| | (0.0278) | (0.0287) | (0.0288) |
| *COVID Deaths* | 0.0173*** | 0.0097** | 0.0107** |
| | (0.0045) | (0.0046) | (0.0046) |
| *Shadow Economy* | 0.0065* | –0.0010 | –0.0012 |
| | (0.0036) | (0.0037) | (0.0037) |
| *Number of EFT-POS Terminals per Thousand People* | 0.0004 | –0.0029* | –0.0021 |
| | (0.0015) | (0.0016) | (0.0016) |
| *Net Fear of Cash* | 0.2617*** | | 0.2273*** |
| | (0.0253) | | (0.0270) |
| *Change in Habits Related to Physical Contact* | | 0.5853*** | 0.5690*** |
| | | (0.0304) | (0.0307) |
| *Change in Online Habits* | | 0.0605** | 0.0614** |
| | | (0.0258) | (0.0262) |
| Constant | –1.0988*** | –0.6081*** | –0.6986*** |
| | (0.1734) | (0.1804) | (0.1830) |
| Observations | 5,504 | 5,504 | 5,504 |
| chi2 | 436.8 | 587.3 | 609.2 |
| p-value | 0 | 0 | 0 |
| McFadden's Pseudo R-squared | 0.122 | 0.203 | 0.221 |

**Note:** This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

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