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Payment Habits During COVID-19: Evidence from High-Frequency Transaction Data

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Acknowledgements

Abstract

We investigate how the COVID-19 pandemic has changed consumers' payments habits in Canada. We rely on high-frequency data on cash withdrawals and debit card transactions from Interac Corp. and Canada's Automated Clearing Settlement System. We construct daily measures of payment habits reflecting cash usage, average transaction values, and the share of transactions in which the customer or card holder and the acquiring machine (ATM or POS) are of the same bank. Using simple dummy regressions and local projection models, we assess how these indicators of payment habits have changed with the evolution of the COVID-19 pandemic. We find evidence that during the pandemic consumers adjusted their behaviour by avoiding frequent trips for cash withdrawals and point-of-sale purchases and making fewer transactions for higher amounts. They also made smaller-value cash withdrawals compared with the value of card payments, which could reflect a reduced use of cash for point-of-sale transactions. Consumers also made relatively more withdrawals from ATMs that are linked to their financial institution (on-us transactions). Finally, we highlight that estimates of economic activity based on card data alone could be biased if shifts in payment habits are not taken into account. We estimate that debit card payments might have overstated consumer expenditure growth by up to 7 percentage points over the course of the pandemic.

Topics: Coronavirus disease (COVID-19); Payment clearing and settlement systems; Recent economic and financial developments; Domestic demand and components
JEL codes: C22, C55, D12, E21, E42, E52

1 Introduction

The COVID-19 pandemic and the measures to contain it have shifted how much consumers spend, what they spend on and which payment methods, in particular cash, they use when they spend. Understanding these changes is essential to the core mandates of many central banks as they need to assess the state of the economy and issue currency in the form of banknotes or coins. The rapid developments during COVID-19 have highlighted that traditional indicators often lack immediacy and convey an incomplete picture. Since the start of the COVID-19 pandemic, the Bank of Canada and other central banks have thus accelerated the use of alternative data sources. For example, Huynh et al. (2020) obtained alternative weights for the consumer price index from high-frequency expenditure network data on card payments.

This paper uses high-frequency transaction data to assess how consumers' payment habits have adjusted to the COVID-19 pandemic. Understanding changes in payment behaviour is not only important for monitoring cash demand but also allows us to shed light on the reliability of this transaction data in assessing the state of the economy. A shift in payment habits may affect the dynamics of consumer spending as measured by card payments. For example, shifts from cash towards debit cards could imply that actual spending could be overestimated by card payments. Quantifying how cash use has evolved relative to electronic payment methods during the pandemic is thus key in understanding the link between high-frequency transaction data and consumption.

In particular, we use a comprehensive dataset based on data for ATM withdrawals and point-of-sale (POS) debit card transactions from two payment infrastructure providers in Canada, Interac Corp. and the Automated Clearing Settlement System (ACSS). We construct daily measures of payment habits, such as the share of cash transactions and average transactions values. The transaction data from Interac and ACSS also allows us to obtain a measure of so-called "on-us" transactions—those transactions in which the customer or card holder and the acquiring machine like ATM or POS are of the same bank. We discuss how these measures have evolved throughout the pandemic and support

these observations with simple dummy regressions. Further, we assess the link between the COVID-19 pandemic and payment habits more formally using local projection models at daily frequency. We obtain impulse responses for each measure of payment habits to changes in indicators of the pandemic such as new confirmed cases and the stringency of government-imposed response measures. Finally, we provide insights on how a shift from cash towards debit cards affects the dynamics of card transactions, and we calculate the potential bias if debit card payments were used as a proxy for consumption expenditure.

Our work contributes to several strands of ongoing research: First, recent studies have illustrated the usefulness of electronic payments data in monitoring the state of the economy for a number of countries, e.g., Galbraith and Tkacz (2013), Galbraith and Tkacz (2018), Chapman and Desai (2021) for Canada, Aastveit et al. (2020) for Norway, Cavallo (2020) for the US, and Aprigliano et al. (2019) for Italy. These papers mostly assess whether high-frequency card transaction data can improve forecasts of economic variables such as GDP and consumption. However, they abstract from the role of cash and how shifts in payment behaviours may influence the reliability of this data for monitoring the economy.

Second, our paper contributes to the literature analyzing the response of cash following shocks that directly or indirectly affect its use. This literature has documented how payment habits change following government-imposed measures directly restricting cash use. One prominent example is the Indian demonetization in 2016, when the Indian government removed the legal tender status of 86% of the Indian currency in a surprise announcement and introduced new banknotes with legal tender status. The stated goals of this policy were to curb the underground economy and remove counterfeit banknotes from circulation. Lahiri (2020) considers the aggregate change in indicators of payment habits such as currency in circulation and the use of digital payments. He concludes that currency in circulation recovered within months and the adoption of digital payments was lower than expected. Further, Chodorow-Reich et al. (2019), using geographical variation in the severity of demonetization, show that a sharp, temporary decline in currency reduced ATM withdrawals and economic activity while encouraging adoption of alternative payment technologies.

Another case is the Greek government's imposition of daily ATM withdrawal limits

2

during the Greek debit crisis in 2015, which lasted until 2019. At the same time, measures were put in place to increase electronic payments and discourage cash. While electronic payment methods have substantially increased at the POS (European Payments Council, 2019), Greece is still among the most cash-intensive countries in the EU (Esselink and Gijsel, 2017).

The COVID-19 pandemic is different from the former cases in the sense that there has been no imposition of direct restrictions on cash behaviour. Chen et al. (2020) find that cash use fell in the early stages of the pandemic when lockdown measures were in place and increased during the reopening in the summer of 2020, indicating that consumers may have adjusted their payment behaviour without direct restrictions on cash use.

Our analysis shows that with the COVID-19 pandemic, cash withdrawals, especially withdrawals from ATMs not belonging to the cardholder's bank, have dropped in comparison to debit card transactions. This decline is more pronounced for the total transaction value, although the average dollar value of both cash withdrawals and card transactions has increased. At the same time, a larger share of POS debit card transactions now involves a consumer and a merchant who do not have their accounts with the same financial institution (FI).

We find evidence that consumer behaviour adjusted to the pandemic by avoiding frequent trips for cash withdrawals and POS purchases and making fewer transactions for higher amounts. The increased amounts for ATM withdrawals (especially during the first lockdown) could also reflect an increase in cash demand related to precautionary motives. Further, consumers withdrew less cash compared to card payments, which may reflect a reduced use of cash for point-of-sale transactions. In addition, consumers made relatively more withdrawals from ATMs that are linked to their FI (on-us transactions), possibly because they planned their withdrawals or because they could not access white-label ATMs that are often located inside of businesses. The larger share of on-us transactions could also be explained by reduced mobility which kept consumers close to their "home bank." These reasons are consistent with a decrease of the on-us share during the reopening of businesses and the lifting of mobility restrictions. Finally, the share of non-on-us debit POS transac-

tions increased during the pandemic. Consumers are probably unaware of whether a card payment is non-on-us or on-us. However, shifts towards e-commerce and larger retailers as well as closures in certain industries might have impacted FIs' issuing and acquiring lines in an asymmetric way, hence leading to changes in their non-on-us shares. Microdata from consumers and businesses or FIs could deliver more insights.

While generally our measures of payment habits have not yet returned to pre-pandemic levels, their behaviour seems to be linked to the evolution of the pandemic. For example, the use of cash increased over the summer of 2020 (when there were relatively low and stable COVID-19 case counts) and decreased again towards the end of the year (when Canada entered the second wave). However, it is not yet evident from our dynamic analysis whether this behaviour is in line with temporary changes or a sign of a persistent shift away from cash and also towards withdrawals at FI-owned ATMs.

Finally, our findings highlight that estimates of economic activity based on card data alone could be biased if shifts in payment behaviour, such as a change in cash use, are not taken into account. For example, growth in consumer spending could be mis-estimated from card transaction data as payment choices seemed to change during the pandemic. We estimate that debit card payments might have overstated expenditure growth by up to 7 pp over the course of the pandemic.

The paper proceeds as follows. In Section 2 we describe the transaction data and the COVID-19 indicators used in our analysis. Section 3 introduces our measures of payment habits and provides first insights on their evolution amid COVID-19. Section 4 shows a more formal analysis based on dummy regressions and local projection models. We also assess by how much consumption expenditures could be biased were they proxied by debit card transactions alone. Section 5 concludes.

2   Data

We start this section by introducing the high-frequency transaction data based on Interac and ACSS ABM withdrawals and debit card transactions. We then present the indicators

that we use to describe the severity and state of the COVID-19 pandemic.

2.1 Transaction Data

Data on cash withdrawals and debit card transactions comes from two payment infrastructure providers, Interac Corp. and the ACSS. We start by describing the schematic presented in Figure 1. To distinguish the roles of these infrastructures, we explain on-us transactions. Electronic payment card transactions such as cash withdrawals at ABMs and debit cards transactions at a POS terminal involve four parties. On the so-called issuing side there are two parties: the cardholder and the financial institution (FI) where the bank account linked to the card is held. On the acquiring side, there are also two parties: the owner of the POS terminal or the ABM and the financial institution of the owner. On-us transactions involve the same financial institution on the acquiring side and the issuing side. For example, if someone withdraws cash at an ABM that belongs to the same bank that issued the card, then the transaction is on-us. If the person uses their card at a merchant who has their account with a different financial institution, then the transaction is not on-us.

Interac Corp. operates the main debit card network in Canada, which consists of the shared Inter-Member Network (IMN) for ABM withdrawals and another shared IMN for debit purchases at the point of sale. All ABM withdrawals and debit purchases, on-us and non-on-us, made with Interac debit cards are processed through the shared IMN.[1] Merchants also need a payment processor to clear and authorize debit purchases. The ACSS further clears the non-on-us transactions that are processed and authorized by the IMN and for which the issuer and acquirer are different members of the shared network.[2]

Besides Interac cash withdrawals and the Interac debit payments at a POS terminal discussed here, Interac Corp. also offers Interac online debit payments and Interac e-transfers. E-transfers can be used to transfer funds using the mobile phone number or email address of the recipient. Likewise, the ACSS also clears other non-on-us e-transfers and other

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[1]IMN participants are either direct connectors with a physical connection to the IMN or indirect connectors whose transactions are routed through a direct connector.

[2]Many Interac debit cards in Canada are co-badged as Visa Debit cards. Transactions at a physical POS made with these cards that are entered as Visa Debit are also processed by Interac, and the same distinction between on-us and non-on-us applies.

electronic items such us pre-authorized debit and credit, as well as paper items (cheques).

We will now explain in more detail the streams, or transaction flows, used in our analysis.

Interac: For cash transactions, the Interac data includes withdrawals at ABMs connected to the IMN. These ABMs could be on the premises of an FI, FI-owned offsite, or white-label ABMs.[3] The POS purchases in the Interac dataset consist of Interac debit payments made at a physical payment terminal, including chip- and pin-authorized transactions and contactless Interac Flash transactions. The data is already adjusted for refunds and cases where an ABM did not contain enough banknotes to cover the requested amount. Data is available for every calendar day, including weekends and holidays.

ACSS: In the ACSS terminology, the transactions considered in our analysis are called point-of-service payments because they most commonly involve using a payment card at a physical service point which is either an ABM or a payment terminal. ABM transactions are split into two streams: the first one is the "pull" that happens when a cardholder requests a certain amount of cash from an ABM. The second one is an adjustment stream that accounts for situations where the ABM does not contain enough banknotes to cover the requested amount. Similarly, two separate streams exist for in-store debit payments, one for payments and one for refunds. Each stream provides the dollar value and the number of transactions. We subtract these refunds and adjustments from purchase quantities and requested ABM quantities, respectively, to obtain the numbers used in this paper .

ACSS data is available on a daily frequency for the days when the ACSS operates. The ACSS operates Monday to Friday except for holidays. Relative to the time when the cardholder initiated the transaction at the point of service, the ACSS clears the transaction with a delay.[4][5]

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[3]See CBA: https://cba.ca/abm-market-in-canada.

[4]A transaction on a day when the ACSS is open is assumed to clear on the first day after the transaction that the ACSS is also open. If the transaction takes place on a day when the ACSS is closed, it is assumed to clear on the second day after the transaction that the ACSS is also open.

[5]Financial institutions may prefer on-us transactions because they do not experience a delay in settlement and because they are not exposed to the risk that another financial institution cannot meet its obligation (Northcott, 2002).

2.2 COVID-19 Indicators

To measure the pandemic's intensity and evolution, we consider a few alternative indicators: government stringency and COVID-19 cases. The data for government stringency and COVID-19 cases is taken from the COVID-19 dataset collection maintained by Our World in Data (Roser et al., 2020). The COVID-19 government stringency index is part of the Oxford COVID-19 Government Response Tracker (see Hale et al., 2020).[6] It is a composite measure of nine responses indicators—school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls—rescaled to a value from 0 to 100 (100 = strictest).[7] Daily data for confirmed COVID-19 cases originates from the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University.

Figure 2 shows the evolution of these indicators over our sample period (January 1st, 2019–February 26th, 2021). The first wave of the pandemic in the spring of 2020 led to strict government measures that were eased partially over the summer due to relatively stable new case counts. In the fall, Canada entered the second wave as new cases and the positivity rate increased.

3 Measures of Payment Habits and First Insights

3.1 Cash-Card Ratios

To measure one of the aspects of payment habits related to cash usage, we calculate the cash-card ratio. The cash-card ratio has been used as a proxy for the share of cash transactions at the POS (see, e.g., Rocco, 2020). The ratio of cash withdrawals to card transactions (cash-card ratio) is constructed by dividing the amount of ABM cash transactions by the amount of POS debit transactions. We observe that the cash-card ratio is higher in the

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[6] It is important to note that this index simply records the strictness of government policies. It does not measure or imply the appropriateness or effectiveness of a country's response.

[7] If policies vary at the sub-national level, the index is shown as the response level of the strictest sub-region.

Interac data than in the ACSS data (Figure 3) before and during the pandemic. This is explained by our later discussion of the ACSS-Interac ratios; namely, the proportion of on-us ABM withdrawals in 2019 was about three to four times larger than the proportion of on-us POS payments in the same time period. In the Interac data, we find therefore that in the pre-pandemic period the value of banknotes withdrawn relative to debit card payments was about 43%, while the ratio is approximately 13% in the ACSS data. With the onset of the pandemic in March 2020, the value and volume ratios drop in both data series but remain below pre-pandemic averages until the end of our sample. Their behaviour also seems to be linked to the evolution of the pandemic. For example, the cash-card ratio increased somewhat over the summer of 2020 (when there were relatively low and stable COVID-19 case counts) and decreased again towards the end of the year (when Canada entered the second wave).

In addition to transaction data, central banks mostly rely on surveys to estimate the share of cash transactions. To that end, we compare the cash-card ratio based on debit card transactions to estimates derived from Canadian survey data for the year 2017. Specifically, Henry et al. (2018) estimate the value share of cash transactions at the POS at 16% and the volume share at 33%, relative to debit card shares of 26% for the value and 24% for the volume. From these estimates, the value share of cash transactions would be around 38%, obtained by dividing the cash value share of 16% by the sum of the value shares of cash and debit (26%). By contrast, the cash-card ratio in the Interac data would imply a value share of 30%.[8]

Several factors may explain the 8 pp higher cash share in the survey data than in the Interac data: First, while Henry et al. (2018) report that ABM withdrawals are the most common way to obtain banknotes, bank teller withdrawals and cash-back withdrawals during a debit card purchase also play a significant role. Second, using withdrawals in the cash-card ratio ignores the possibility that the same banknote is used in several cash transactions before it is deposited at an FI. On the other hand, there are also factors that would support a higher cash-card ratio constructed from point-of-sale transactions in the survey

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[8]The cash-card ratio implies that the value of ATM withdrawals is 0.43 times the value of debit card transactions. Hence the value share of cash is $0.43/(1 + 0.43) = 0.30$.

data than the cash-card ratio constructed from ATM withdrawals. First, individuals also withdraw and hold cash for non-transactional purposes (savings, precautionary motives). Second, cash is also used for person-to-person transactions. Third, Henry et al. (2018) observe a downward trend in the value share of cash transactions, which might indicate that the cash-card ratio at the POS in 2019 might be lower than in the 2017 survey.

3.2   Average Transaction Values

We also consider average transaction values as another aspect of payment habits. Average transaction values are calculated as the transaction value for a given day divided by the transaction volume for the same day. In 2019, a typical ATM withdrawal amount was around $178 in the Interac data and about $145 in the ACSS data (see Figure 4). The data shows an upward shift in the size of withdrawal between January and February 2020. The gap between Interac and ACSS withdrawal increased at the onset of the pandemic. Also, both series seem to co-move with the intensity of the pandemic. By contrast, the typical debit card transaction processed by Interac was around $39, close to the typical value of $38 for the ACSS. Overall, both POS averages increase and remain highly correlated over the duration of the pandemic thus far.

3.3   ACSS-Interac Ratios

We calculate the ACSS-Interac ratios for ATM withdrawals and POS transactions to gauge the non-on-us transactions. To do so, we create a second harmonized dataset from the Interac streams by aggregating processed amounts by the day that they would have been cleared by the ACSS. For example, we aggregate Interac transactions from Saturday, Sunday and Monday and compare them to ACSS transactions for Tuesday. Tuesday's Interac transactions are compared to Wednesday's ACSS observations. This dataset allows us to compare Interac and ACSS data at the daily frequency and to calculate the ratios.

Figure 5 shows the Interac-ACSS ratios over time. For 2019, 22% of the value of ABM transactions was cleared by the ACSS; correspondingly, 78% of the value was contributed by on-us transactions. For the volume, 28% of the withdrawals were cleared by the ACSS (72%

9

on-us transactions). In other words, cardholders most commonly make on-us withdrawals, and they withdraw higher amounts during on-us transactions than during non-on-us transactions.

A likely explanation is that cardholders can often avoid account fees and other charges if they make withdrawals at an ABM affiliated with the issuer of their card. Also, bank-owned ABMs might allow for higher withdrawal amounts since the owner of the white-label ATM might set the maximum withdrawal amount below the maximum set by the card issuer.

During the pandemic, the ACSS-Interac ratios for cash plunged during the first lockdown, increased during the reopening, and fell again during the second lockdown (Figure 5, red lines). Turning to POS debit payments, the share of non-on-us POS debit transactions was quite steady around 80% for the value. While the volume share averaged around 83% in 2019, it increased during the second half of that year. The cardholder is usually unaware of which FI will acquire a card payment, but changes in the concentration on the issuing or acquiring side can still drive this share of non-on-us card payments. In contrast to cash, the ACSS-Interac ratio for these transactions steadily increased over the course of the pandemic (Figure 5, blue lines).

4 Empirical Approach

To analyze the changes in payment habits throughout the COVID-19 pandemic more formally, we use two approaches. First, we employ a static dummy regression. Then, we estimate a local projection model to assess the dynamic effects of our COVID-19 indicators.

4.1 Static Model: Dummy Regressions

We use a simple dummy regression to explore the change in the variables of interest during different phases of the pandemic. This allows us to quantify the shift in each COVID-19 phase compared to the pre-pandemic period (2019 to early 2020) that we observed in the previous section.

We roughly define four phases: lockdown 1 (March 2020–April 2020), reopening 1 (May

2020–October 2020), lockdown 2 (November 2020–January 2021), reopening 2 (February 2021).[9] We construct four dummies, one for each phase. We control for seasonal patterns and trends by including day-of-week, week-of-month, and month-of-year dummies.[10] We regress the variables of interest described in the former section on the COVID-19 phase dummies, seasonal dummies, and a constant over a daily sample covering January 1st, 2019–February 26th, 2021.

The cash-card ratios both in value and volume terms decreased over the pandemic. Cash-card value ratios were up to 9 pp and 6 pp lower for Interac and ACSS transactions, respectively.

Average transaction values increased during the pandemic. For cash withdrawals, the average withdrawal size increased by up to 31% in the Interac data and by up to 15% in the ACSS data. In both datasets, the average withdrawal amount was highest during the first lockdown and decreased afterwards (while remaining above pre-pandemic levels). Similarly, the average value of a POS debit card payment increased by 11% and 12% for the Interac data and ACSS data, respectively, during the first lockdown and remains elevated.

Overall, the ACSS-Interac ratio decreased over the pandemic for cash and increased for card transactions. For cash, the ratio was up to 6 pp and 4 pp lower for the value and the volume, respectively. For cards, the increase was up to 4 pp for the value and up to 6 pp for the volume (Table 2).

4.2   Dynamic Model: Local Projections

To evaluate the dynamic effects and their persistence during the pandemic, we use the local projection impulse response estimator introduced by Jordà (2005). We obtain the impulse responses of our variables of interest to the COVID-19 indicators by estimating the following

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[9]The phases are motivated by the behaviour of cases and stringency across Canada. For example, we roughly define the lockdown phases as periods when COVID-19 cases are increasing and provincial governments such as Ontario imposed lockdown measures. Since lockdowns have not been imposed at the national level, the phases may have varied at the provincial level. The phases defined here are, thus, a rough generalization at the national level.

[10]In the case of Interac, we also need a day-of-month dummy to fully control for seasonal patterns. Since the ACSS data comes at the business-day frequency, we also include dummies for the day of the business week.

regressions over our daily sample from January 1st, 2019–February 26th, 2021:

$$y_{t+h} = a_h + \sum_{i=1}^{p} b_{i,h} y_{t-1} + c_h x_t + e_{t+h}, \quad h = 1, ..., 100, \tag{1}$$

where y_{t+h} is our variable of interest (cash-card value and volume ratios, logarithms of average ABM and POS transaction values, ACSS-Interac ABM value and volume ratios, and ACSS-Interac POS value and volume ratios), x_t is one of the two exogenous COVID-19 indicators (logarithm of COVID-19 cases or logarithm of the government stringency index), and p is the number of lags. We assume that the COVID-19 indicators are exogenous since it is unlikely that transactions affect these indicators (by affecting the transmission of the virus) at the daily frequency. However, endogeneity concerns can become relevant at lower frequencies.

As before, we control for seasonal patterns by including day-of-week, day-of-month, week-of-month, and month-of-year dummies. To render the responses of ACSS and Interac variables comparable in terms of timing, we use the Interac data harmonized to business-day frequency. The estimation includes 10 lags, corresponding to two weeks.[11] We consider horizons of up to 100 business days.

Figure 6 shows impulse responses for the cash-card value and volume ratios to the two COVID-19 indicators. We find that a 100% increase in new cases results in a drop of 0.4 pp on impact in the cash-card value ratio. The responses reach their peak at about -0.9 pp and -1.5 pp for the ACSS and Interac transactions, respectively. While the response of the cash-card ratio measured by ACSS data reverts after about 40 business days (although not to pre-shock levels), the cash-card value ratio measured by Interac data continues to fall.

Similar patterns arise when looking at the responses to an increase in the stringency index. The Interac cash-card value ratio falls by between about 0.7 pp and 2.5 pp following a 100% increase in the stringency index over a horizon of about 80 business days. The ACSS cash-card value ratio decreases by between 0.8 pp and 1.7 pp over a horizon of about 40 business days. Again, the responses of the cash-card value ratios based on Interac and

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[11]Note that responses are similar when we consider a smaller number of lags.

ACSS start to diverge after about 40 business days.

Similar patterns are observed if we consider the responses of the cash-card volume ratios to an increase in cases and the stringency index. However, the responses following an increase in cases revert somewhat to pre-shock levels, albeit not significantly.

Turning to the dynamic responses of ABM average transaction values, we find that following a 100% change in the stringency index, the ABM average transaction value measured by ACSS increases by about 2 pp over all horizons (see Figure 7, panels a and b). The response of ABM average transaction values based on Interac is similar on impact but reaches a maximum of about 8 pp after about 40 business days. Similar responses arise, although slightly less pronounced, following a percent change in COVID-19 cases. The observed difference between the dynamic responses of ABM average transaction values measured by ACSS and Interac is in line with the point made earlier: following the onset of the pandemic, there were relatively more and higher-value on-us ABM withdrawals versus non-on-us.

POS average transaction values obtained from ACSS and Interac behave very similarly in response to a change in stringency and cases (Figure 7, panels c and d). While persistently positive, the responses start to revert after about 40 business days.

We now discuss the responses of the ACSS-Interac ratios reflecting the behaviour of non-on-us transactions over the pandemic (Figure 8).[12] A change in stringency decreases the ACSS-Interac ratio for ABM withdrawals in both value and volume terms. The responses start to revert after about 40 business days, although they do not recover to pre-shock levels. The observed dynamic responses of the ACSS-Interac ratio, therefore, support our claim that the differences in responses between ACSS and Interac data over the pandemic are related to the distinct behaviours of non-on-us and on-us transactions throughout the pandemic.

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[12]For the sake of brevity, we show only impulse responses to a change in stringency. The responses to a change in COVID-19 cases are very similar.

4.3 Adjustment to include cash transactions

How cash has evolved relative to card payments is key in understanding the link between high-frequency transaction data and household spending. Estimates of economic activity based on card transaction data alone could be biased if shifts in payment behaviour, such as a change in cash use, are not taken into account. For example, growth in consumer spending could be mis-estimated from card transaction data as payment choices seem to have changed during the pandemic. In what follows, we illustrate how the cash-card ratio is relevant for linking card payment data to nominal household expenditure. We provide insights on how a shift from cash towards debit cards affects the dynamics of cards payments and calculate the potential bias if debit card payments were used as a proxy for consumption expenditure.

We construct two proxies for growth in nominal expenditure, i.e., one based on the value of POS debit card transactions alone and one adjusted for cash (sum of cash and debit card transactions).[13] In what follows, we base our results on the Interac data because it has a better coverage of transactions compared to the ACSS data and also because the cash share in the Interac data is closer to, e.g., the cash share based on survey data in Henry et al. (2018). In particular, the growth rates in expenditure between time t_1 and t_2 based on the value of POS debit card transactions alone (g_{card}) and adjusted for cash (g_{adj}) are given by:

$$g_{card} = \frac{Card_{t_2}}{Card_{t_1}} - 1;$$
$$g_{adj} = \frac{Card_{t_2} + Cash_{t_2}}{Card_{t_1} + Cash_{t_1}} - 1 = \frac{1 + y_{t_2}}{1 + y_{t_1}}(g_{card} + 1) - 1,$$

where y_t denotes the cash-card ratio. Note that in the formula for g_{adj}, the quantity $1 + y_t$ is the inverse of the card share at time t since $1 + y_t = 1 + \frac{Cash_t}{Card_t} = \frac{Card_t + Cash_t}{Card_t}$.

The difference between g_{adj} and g_{card} reflects the adjustment due to including cash

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[13]Note that therefore our calculations reflect the assumption that all withdrawn cash is used for consumption.

transactions. It can be expressed as:

$$g_{adj} - g_{card} = \frac{1 + y_{t_2}}{1 + y_{t_1}}(g_{card} + 1) - (g_{card} + 1) = \frac{y_{t_2} - y_{t_1}}{1 + y_{t_1}}(g_{card} + 1).$$

Note that $g_{card} + 1 \geq 0$ and $1 + y_{t_1} \geq 0$; hence the direction of the adjustment is given by the sign of $y_{t_2} - y_{t_1}$, the difference in cash-card ratios. Now assume that a series of COVID-19 shocks $x_{t'}$ occur at times t', $t' < t_2$. We decompose the cash-card ratio as $y_{t_2} = \tilde{y}_{t_2} + \Delta_{t_2}$. Here Δ_{t_2} is the sum of all the impulse responses to the COVID-19 shocks (changes in COVID-19 indicators), $\sum_{t'} c_{t_2 - t'} x_{t'}$, and $\tilde{y}_{t_2}$ is the component of y_{t_2} that cannot be explained by these shocks. We can thus rewrite the adjustment as:

$$g_{adj} - g_{card} = \underbrace{\frac{\Delta_{t_2}}{1 + y_{t_1}}(g_{card} + 1)}_{\text{Impulse response to COVID-19}} + \underbrace{\frac{\tilde{y}_{t_2} - y_{t_1}}{1 + y_{t_1}}(g_{card} + 1)}_{\text{residual}}.$$

This decomposition represents the adjustment as the sum of a component explained by COVID-19 shocks and a residual.

Figure 10 shows the evolution of the two growth rates based on transactions in the Interac data since the beginning of 2019. Time is measured in days, and we set $t_1 = t_2 - 364$ to obtain year-over-year (y/y) daily growth rates.[14] Until the onset of the pandemic and during the early phases of the first lockdown, daily y/y card-based and adjusted growth rates are similar, and the adjustment is around -1 pp, likely reflecting a pre-pandemic trend towards card payments. The cash-card ratio falls sharply until July 2020 and reaches -7 pp. While the y/y card-based growth and adjusted growth rates picked up during the summer, the adjusted growth rate still remained below the card-based one. In particular, card-based growth rates would imply positive growth for some of the second half of 2020, although adjusted growth rates might indicate that nominal spending remained below 2019 levels. The adjustment remained at -7 pp from June to August 2020, then increases to -1 pp in December 2020 and falls again to -6 pp in February 2021.

Further, we decompose the cash adjustment for the y/y growth rate during the first 11

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[14]Using 364 as the time step instead of 365 or 366 (for a leap year) ensures that weekday effects are factored out.

15

months of the pandemic into the COVID-19 component and the residual. Since impulse responses are only available for the first 100 business days, we must make assumptions about the shocks for the remaining time period. In Scenario A the shock is assumed to be a simple moving average after the first 100 days, corresponding to persistent shocks. In Scenario B, the simple moving average is multiplied by an attenuation factor of 0.975 for each business day. In Scenario B, the assumption is that shocks are not persistent after 100 business days.

We first consider shocks to the newly reported COVID-19 cases. Scenario A as shown in Figure 11 shows that COVID-19 shocks explain most of the cash adjustment for the period from late May 2020 to early December 2020. However, the first months of the pandemic and also the period of late December 2020 to early January 2021 are characterized by smaller adjustments, although the COVID-19 component is of similar magnitude as in the aforementioned period. A pickup in the cash-card ratio (despite COVID-19 shocks) drives this difference and might be due to non-transactional motives to withdraw cash. For example, precautionary cash holdings increased at the beginning of the pandemic (Chen et al., 2020). Given restrictions on shopping outlets, consumers might also have given cash gifts during the holiday season.

Scenario B for attenuating shocks behaves identically to Scenario A until the 100th business day of the pandemic, by construction. However, afterwards the COVID-19 shocks explain only about half of the cash adjustment between August and December 2020. In contrast, the COVID-19 component explains a large part of the adjustments in December 2020 and January 2021, and a smaller part in February 2021.

The decomposition of the cash adjustment into a COVID-19 stringency component and a residual are shown in Figure 12. While this decomposition is similar to the previous one, the model with attenuating shocks would imply that other factors behind the discrepancy between card-based and adjusted growth rates become more pronounced in the later stage of the pandemic, as the residual falls to around -4 pp.

5 Conclusion

High-frequency data on ATM cash withdrawals and card transactions reveals that, since the onset of the pandemic, cash withdrawals, especially withdrawals from ATMs not belonging to the cardholder's bank, have dropped in comparison to debit card transactions. This decline is more pronounced for the dollar value, although the average dollar value of both cash withdrawals and card transactions has increased. At the same time, a larger share of POS debit card transactions now involves a consumer and a merchant who do not have their accounts with the same FI.

We find evidence that during the pandemic consumers adjusted their behaviour to avoid frequent trips for cash withdrawals and POS purchases. Instead, they performed fewer transactions but for higher amounts. They reduced the value of cash withdrawals compared with the value of card payments, and they performed a smaller number of cash transactions than card transactions. Consumers also made relatively more withdrawals from ATMs that linked to their FI (on-us), possibly because they planned their withdrawals or because they could not access white-label ATMs that are often located inside of businesses. The larger share of on-us transactions could also be explained by reduced mobility which kept consumers close to their home bank. These reasons are consistent with a decrease of the on-us share during the reopening of businesses and the lifting of mobility restrictions. However, neither the cash-card share nor the non-on-us share recovered to pre-pandemic levels during the reopening, and both fell again during the second lockdown. It is not yet evident from our dynamic analysis whether this is due to the short time period between the two lockdowns or is a sign of a persistent shift towards card payments and also towards withdrawals at FI-owned ATMs.

The share of non-on-us debit POS transactions increased during the pandemic. Consumers are generally unaware of whether a card payment is non-on-us or on-us. However, shifts towards e-commerce and larger retailers as well closures in certain industries might have impacted the FIs' issuing and acquiring lines in an asymmetric way, hence leading to changes in their non-on-us shares. Microdata from consumers and businesses or FIs could

17

deliver more insights.

Since card network data has increasingly been used to understand shifting expenditure patterns during COVID-19, the cash-card ratios in the Interac and ACSS data can be used to understand the direction of the bias of the estimated expenditure growth based on card network data. While some caveats apply, the decline in the cash-card ratio might be an indicator that expenditure growth estimated from card network data alone is biased upwards.

References

Aastveit, K. A., Fastbø, T. M., Granziera, E., Paulsen, K. S. and Torstensen, K. N. (2020). Nowcasting norwegian household consumption with debit card transaction data, *Working Paper 17/2020*, Norges Bank.

Aprigliano, V., Ardizzi, G. and Monteforte, L. (2019). Using Payment System Data to Forecast Economic Activity, *International Journal of Central Banking* **15**(4): 55–80.

Cavallo, A. (2020). Inflation with Covid Consumption Baskets, *NBER Working Papers*, National Bureau of Economic Research.

Chapman, J. and Desai, A. (2021). Using Payments Data to Nowcast Macroeconomic Variables During the Onset of COVID-19, *Staff Working Paper 2021-2*, Bank of Canada.

Chen, H., Engert, W., Huynh, K., Nicholls, G., Nicholson, M. and Zhu, J. (2020). Cash and COVID-19: The impact of the pandemic on demand for and use of cash, *Staff Discussion Paper 2020-6*, Bank of Canada.

Chodorow-Reich, G., Gopinath, G., Mishra, P. and Narayanan, A. (2019). Cash and the Economy: Evidence from India's Demonetization, *The Quarterly Journal of Economics* **135**(1): 57–103.

Esselink, H. and Gijsel, L. H.-v. (2017). The use of cash by households in the euro area, *Occasional Paper Series 201*, European Central Bank.

European Payments Council (2019). Greece's steady progress towards a cashless society, https://www.europeanpaymentscouncil.eu/news-insights/insight/greeces-steady-progress-towards-cashless-society. Accessed: 2021-08-15.

Galbraith, J. and Tkacz, G. (2013). Analyzing Economic Effects of September 11 and Other Extreme Events Using Debit and Payments System Data, *Canadian Public Policy* **39**(1): 119–134.

Galbraith, J. W. and Tkacz, G. (2018). Nowcasting with payments system data, *International Journal of Forecasting* **34**(2): 366–376.

Hale, T., Webster, S., Petherick, A., Phillips, T. and Kira, B. (2020). Oxford COVID-19 Government Response Tracker, *Technical report*, Blavatnik School of Government.

Henry, C., Huynh, K. and Welte, A. (2018). 2017 Methods-of-Payment Survey Report, *Staff Discussion Paper 2018-17*, Bank of Canada.

Huynh, K., Lao, H., Sabourin, P. and Welte, A. (2020). What do high-frequency expenditure network data reveal about spending and inflation during covid-19?, *Staff Analytical Note 2020-20*, Bank of Canada.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections, *American Economic Review* **95**(1): 161–182.

Lahiri, A. (2020). The great indian demonetization, *Journal of Economic Perspectives* **34**(1): 55–74.

Northcott, C. A. (2002). Estimating settlement risk and the potential for contagion in canada's automated clearing settlement system, *Staff working papers*, Bank of Canada.
URL: *https://EconPapers.repec.org/RePEc:bca:bocawp:02-41*

Rocco, G. A. . A. N. . G. (2020). A game changer in payment habits: evidence from daily data during a pandemic, *Questioni di Economia e Finanza (Occasional Papers) 591*, Bank of Italy.

Roser, M., Ritchie, H., Ortiz-Ospina, E. and Hasell, J. (2020). Coronavirus Pandemic (COVID-19, *Technical report*, OurWorldInData.org.

URL: *https://ourworldindata.org/coronavirus*

Tables and Figures

Table 1: *Dummy Regressions of Selected Variables: Cash-Card Ratios and Average Transaction Values*

		Cash-Card Value Ratio	Cash-Card Volume Ratio	log(ABM Average Value)	log(POS Average Value)
Lockdown 1	Interac	-0.040*	-0.025*	0.306*	0.110*
	ACSS	-0.041*	-0.012*	0.154*	0.118*
Reopening 1	Interac	-0.085*	-0.029*	0.234*	0.091*
	ACSS	-0.045*	-0.012*	0.079*	0.083*
Lockdown 2	Interac	-0.081*	-0.027*	0.230*	0.093*
	ACSS	-0.050*	-0.012*	0.049*	0.049*
Reopening 2	Interac	-0.109*	-0.031*	0.231*	0.121*
	ACSS	-0.059*	-0.014*	0.051	0.114 *
# of observations	Interac	752	752	752	752
	ACSS	528	528	528	528

*Notes: * denotes significance at the 1% level based on standard errors robust against heteroskedasticity and autocorrelation (HAC) in the residuals. Daily sample from January 1st, 2019 –February 26th, 2021.*

Table 2: *Dummy Regressions of Selected Variables: ACSS-Interac Ratios*

	ABM Value	ABM Volume	POS Value	POS Volume
Lockdown 1	-0.057*	-0.040*	0.003	0.010
Reopening 1	-0.040*	-0.013*	0.016	0.030*
Lockdown 2	-0.057*	-0.025*	0.029*	0.044*
Reopening 2	-0.054*	-0.024*	0.044	0.055*
# of observations	528	528	528	528

*Notes: * denotes significance at the 1% level based on standard errors robust against heteroskedasticity and autocorrelation (HAC) in the residuals. Daily sample from January 1st, 2019–February 26th, 2021.*

Figure 1: *Network Schematic of Interac and ACSS*

Interac: Processing and authorizing an electronic transaction
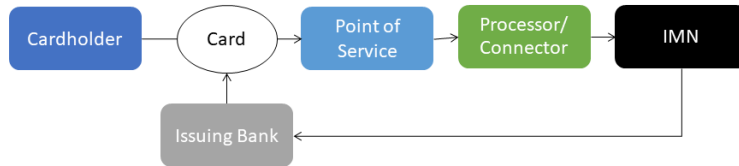
ACSS: Clearing between Issuing and Acquiring Bank

Figure 2: *COVID-19 Indicators: Daily New COVID-19 Cases and Stringency*
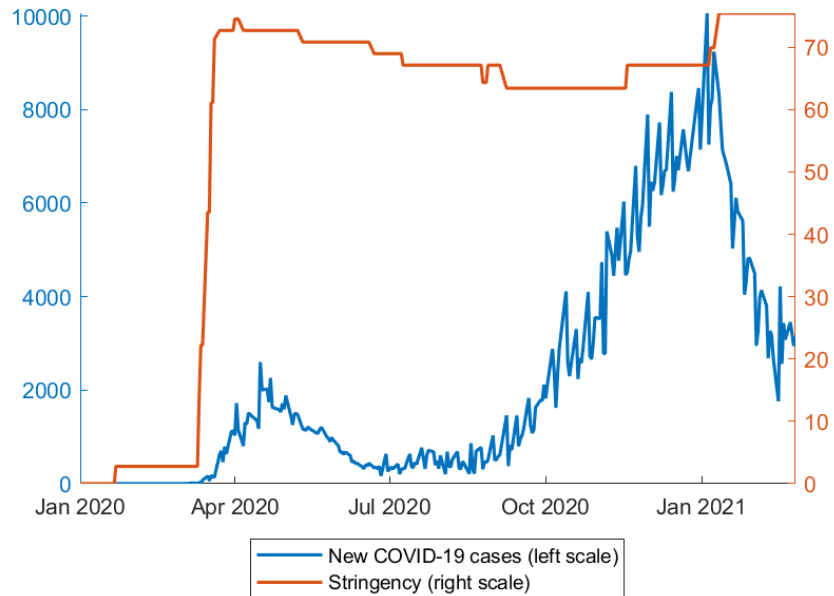
Figure 3: *Cash-Card Ratios*
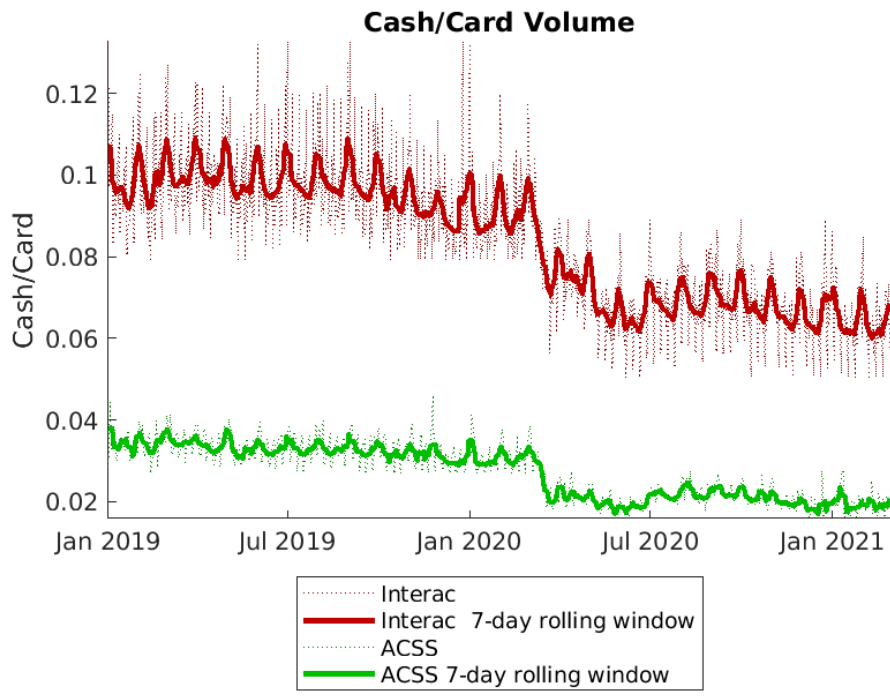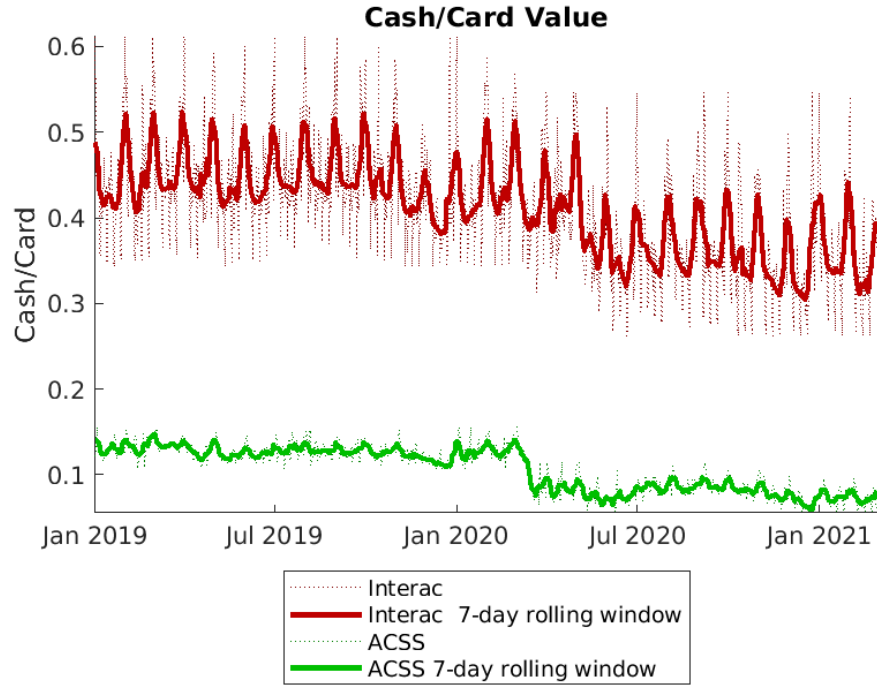

Cash/Card Value

Cash/Card Volume

Notes: Daily values are winsorized at the 2.5 and 97.5 percentiles for presentation purposes. Percentiles are computed separately for the periods before and during the pandemic.

Figure 4: *Average Transaction Values*
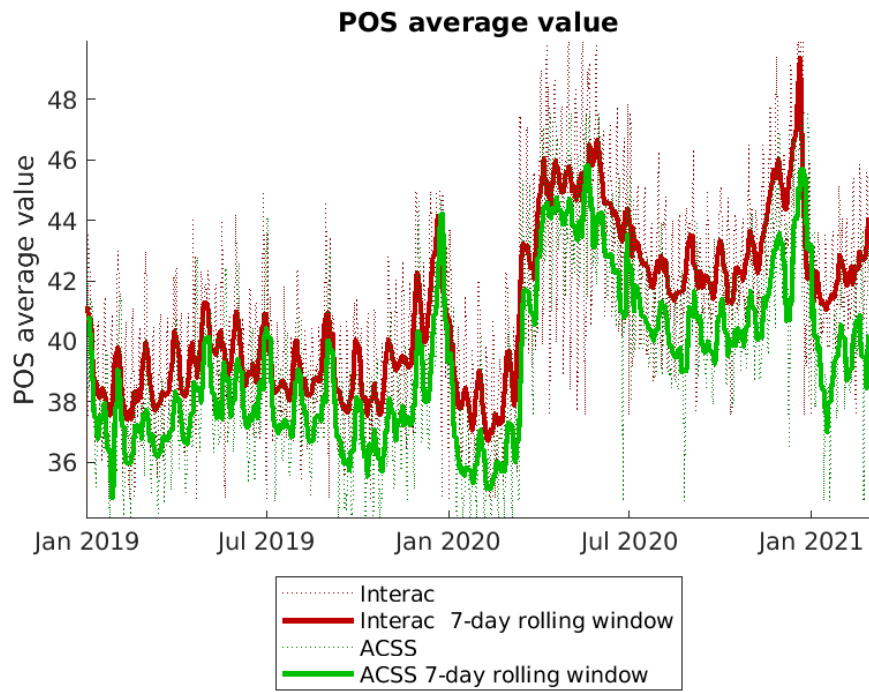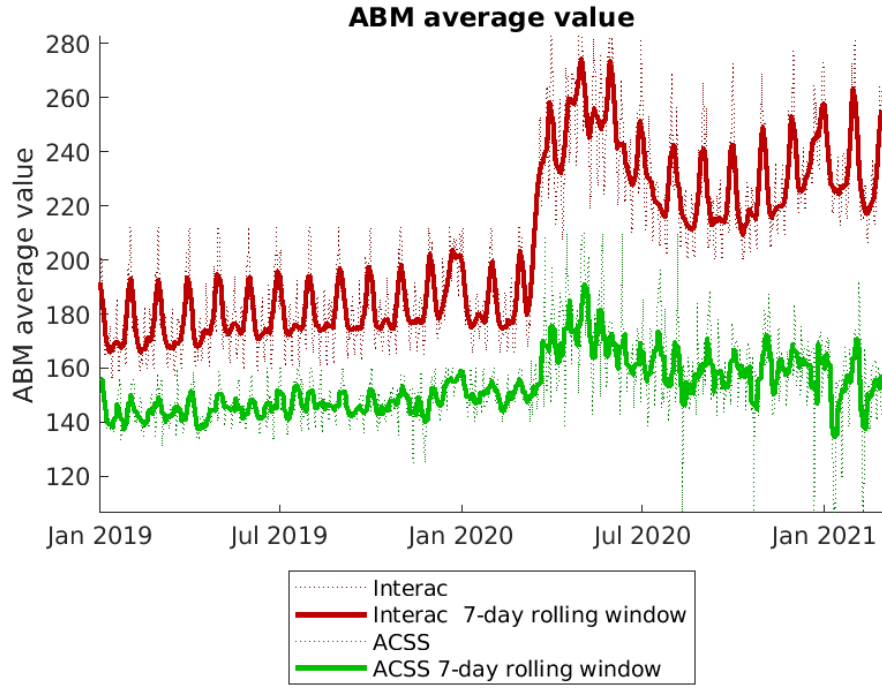
Notes: Daily values are winsorized at the 2.5 and 97.5 percentiles for presentation purposes. Percentiles are computed separately for the periods before and during the pandemic.

24

Figure 5: *ACSS Transactions as a Share of Interac Transactions*
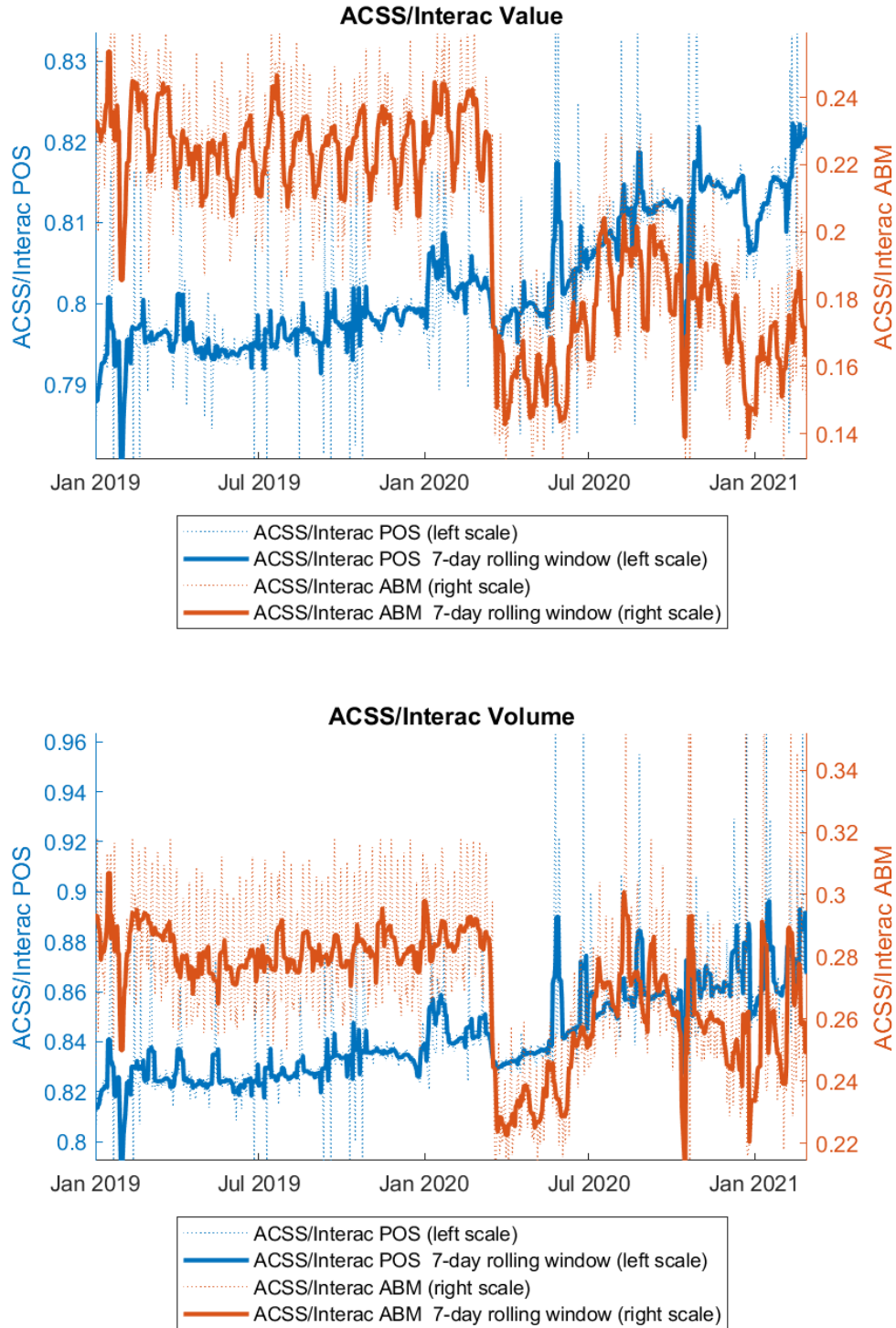
Notes: Daily values are winsorized at the 2.5 and 97.5 percentiles for presentation purposes. Percentiles are computed separately for the periods before and during the pandemic.

Figure 6: *Impulse Responses of Cash-Card Value and Volume Ratios for Interac and ACSS Transactions*

(a) *Cash-Card Ratio: Value Stringency*

(b) *Cash-Card Ratio: Value Cases*

(c) *Cash-Card Ratio: Volume Stringency*

(d) *Cash-Card Ratio: Volume Cases*

Figure 7: *Impulse Responses of ABM and POS Average Transaction Values for Interac and ACSS Transactions*

(a) *ABM Average Value: Stringency*
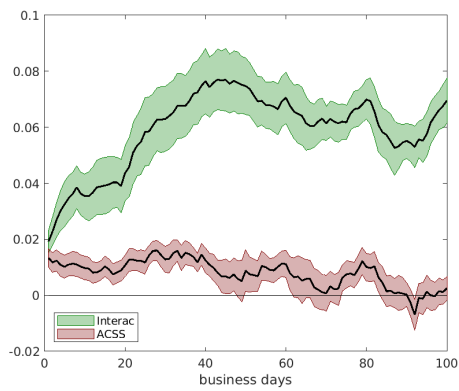
(b) *ABM Average Value: Cases*
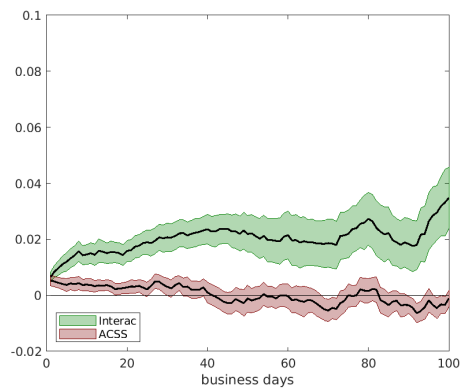
(c) *POS Average Value: Stringency*
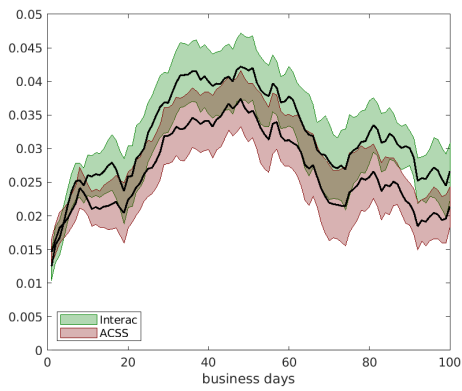
(d) *POS Average Value: Cases*

27
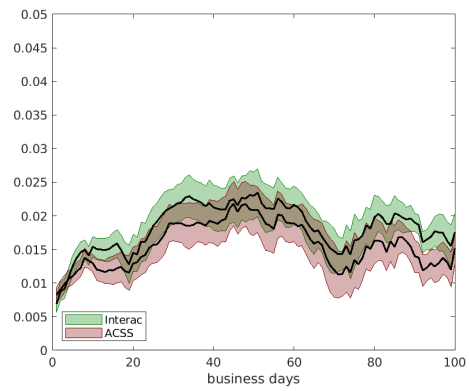
Figure 8: *Impulse Responses of ACSS-Interac Value Ratios for ABM and POS Transactions: Cases*
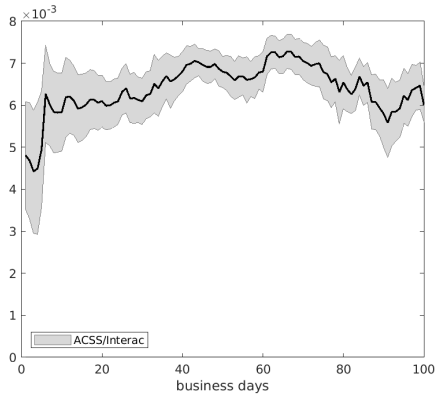
(a) *ACSS-Interac ABM Value: Stringency*
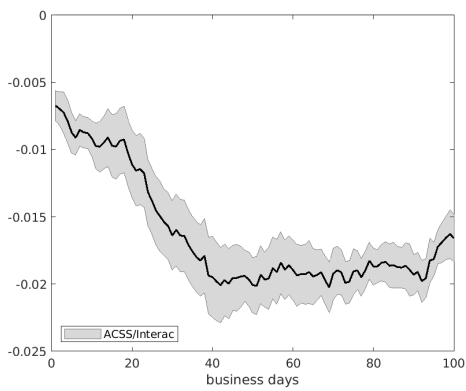
(b) *ACSS-Interac ABM Value: Cases*
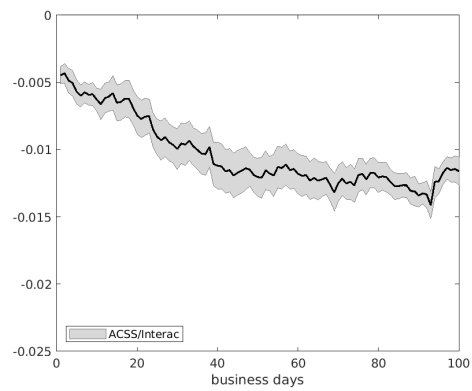
(c) *ACSS-Interac POS Value: Stringency*
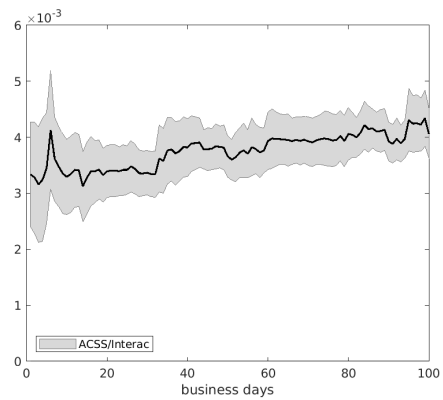
(d) *ACSS-Interac POS Value: Cases*
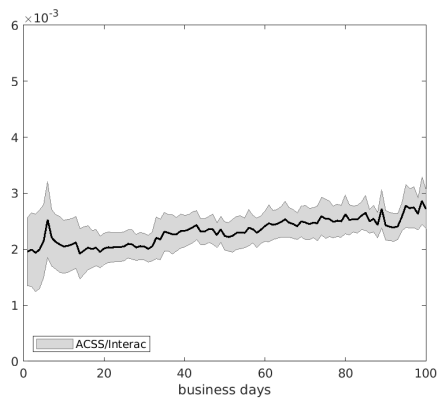
Figure 9: *Impulse Responses of ACSS-Interac Volume Ratios for ABM and POS Transactions: Cases*
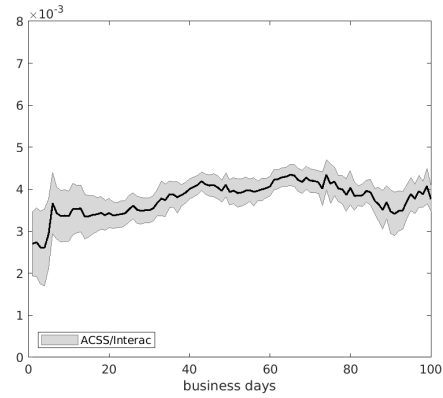
(a) *ACSS-Interac ABM Volume: Stringency*
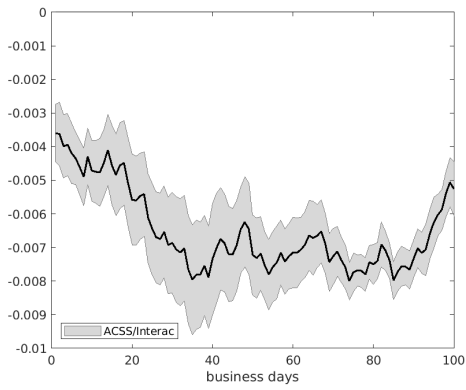
(b) *ACSS-Interac ABM Volume: Cases*
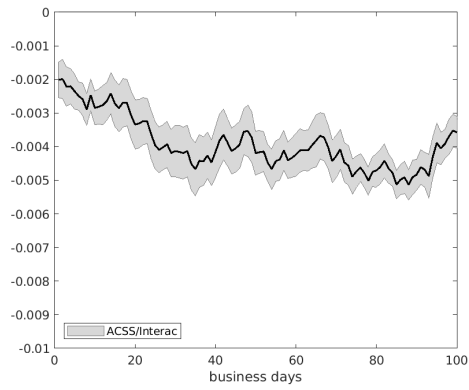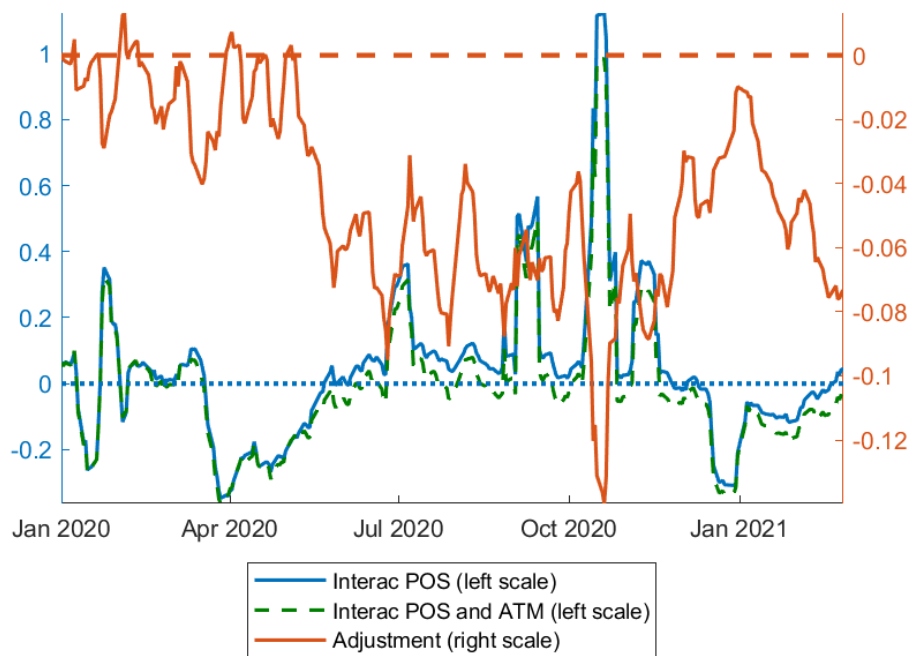

(c) *ACSS-Interac POS Volume: Stringency*

(d) *ACSS-Interac POS Volume: Cases*

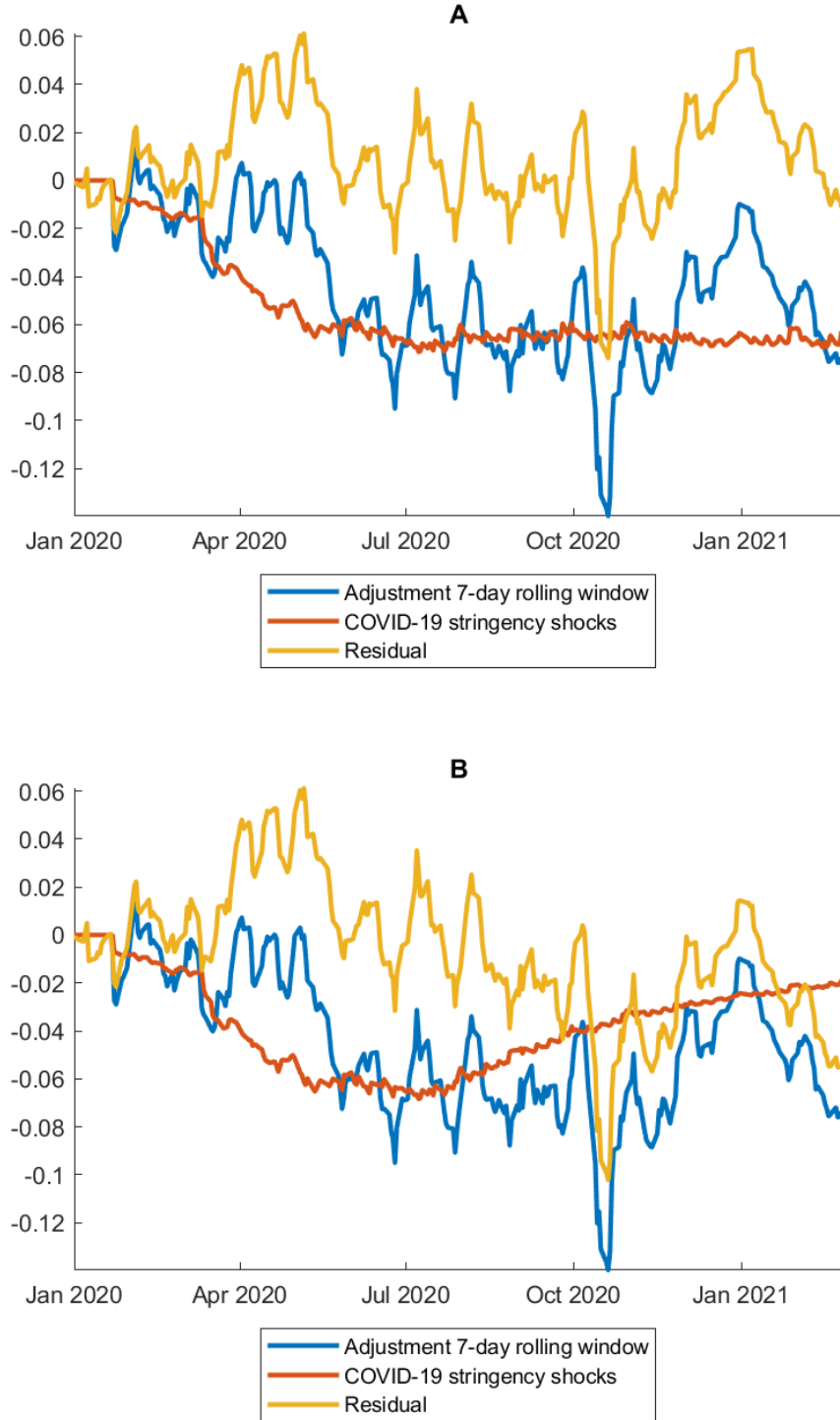**Figure 10:** *Historical Nominal y/y Growth and Adjustments*

Note: The chart displays growth rates and adjustments, computed on a daily basis from the Interac data for POS debit and ATM transactions. Adjusted for the timing of New Year's Eve, New Year's Day, Canada Day, Thanksgiving Day, Remembrance Day, Christmas Eve, and Christmas Day.

Figure 11: *Cash Adjustment Decomposition for Newly Reported Cases*
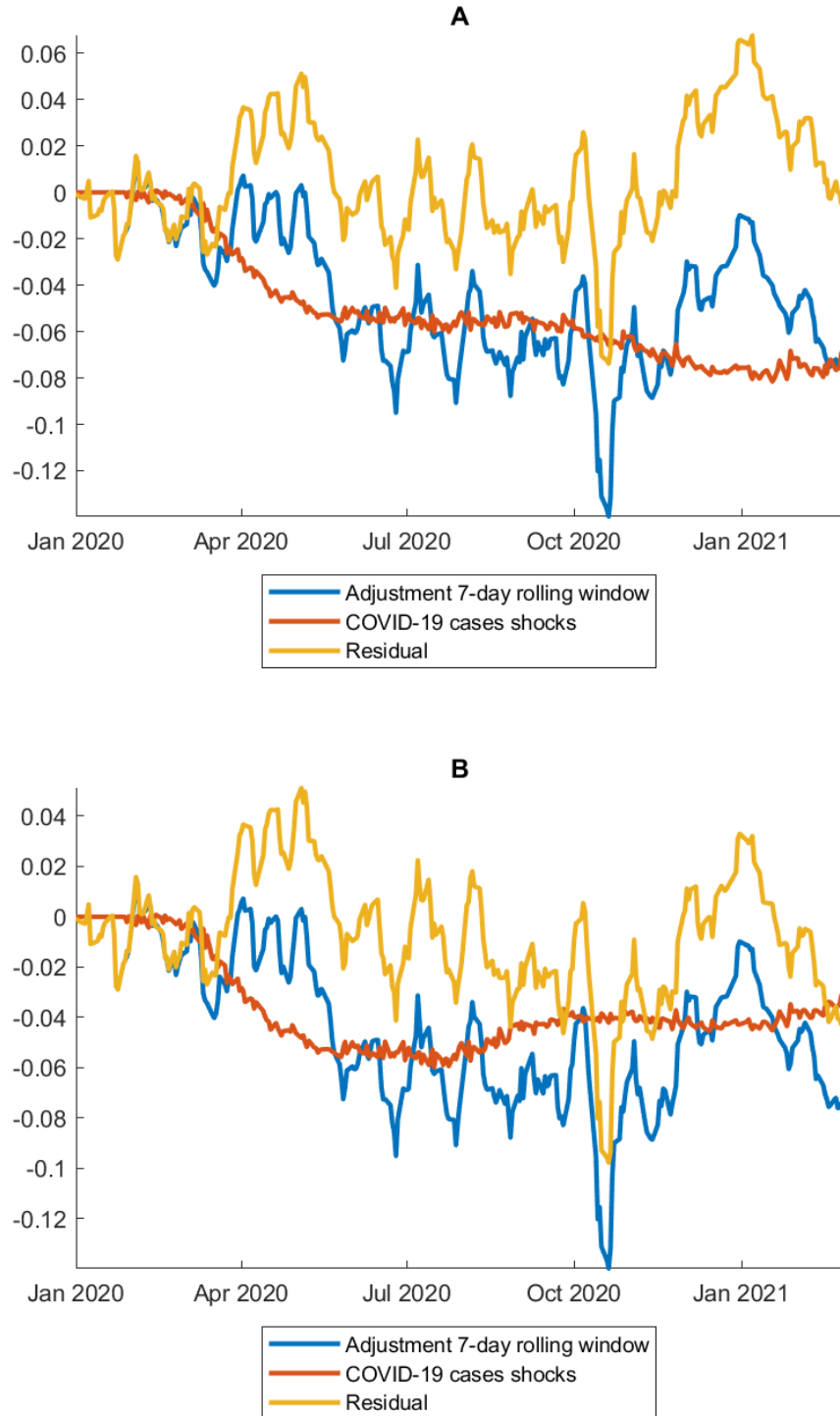
Note: Based on Interac data. Y/Y growth rate adjustments, COVID-19 component and residual. Adjusted for the timing of New Year's Eve, New Year's Day, Canada Day, Thanksgiving Day, Remembrance Day, Christmas Eve, and Christmas Day.

Figure 12: *Cash Adjustment Decomposition for Stringency*

Note: Based on Interac data. Y/Y growth rate adjustments, COVID-19 component and residual. Adjusted for the timing of New Year's Eve, New Year's Day, Canada Day, Thanksgiving Day, Remembrance Day, Christmas Eve, and Christmas Day.