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Nowcasting with payments system data

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ABSTRACT

We consider the potential usefulness of a large set of electronic payments data, comprising the values and numbers of both debit card transactions and cheques that clear through the banking system, for the problem of reducing the current-period forecast ('nowcast') loss for (the growth rates of) GDP and retail sales. The payments system variables capture a broad range of spending activity and are available on a very timely basis, making them suitable current indicators. We generate nowcasts of GDP and retail sales growth for a given month on seven different dates, over a period of two and a half months preceding the first official releases, which is the period over which nowcasts would be of interest. We find statistically significant evidence that payments system data can reduce the nowcast error for both GDP and retail sales growth. Both debit transaction and cheque clearance data are of value in reducing nowcast losses for GDP growth, although the latter are of little or no value when debit data are also included. For retail sales, cheque data appear to produce no further nowcast loss reductions, regardless of whether or not debit transactions are included in the nowcasting model.

1. Introduction

Observations of the current pace of economic activity are crucial to policy-makers and other decision makers, as they can affect, for example, the implementation of counter-cyclical policies or near-term production decisions. However, the most important measure of economic activity, gross domestic product (GDP) growth, is released with a lag (two months in Canada), and is subject to substantial revision. For this reason, policy-makers require reliable current-period estimates ('nowcasts') of GDP growth and other variables in order to monitor economic conditions.

The main contribution of the present study to this problem is its investigation of a broadening of the information set that is at the disposal of nowcasters. We compile, and examine the marginal utility of, a database of the transactions that pass through the payments system, which provides us with information on the values and volumes of debit card transactions, as well as of cheques that clear through the banking system. In addition to providing new proxies for household and business spending, these data have the benefit of being compiled electronically as aggregates of all transactions within a given class, and are therefore available quickly, as well as being virtually free of sampling error. In principle, all such electronic payments can be observed by the investigator. However, in practice the numbers are too large; for example, there are more than 12 million debit transactions per day in Canada. Thus, a high degree of aggregation is necessary for use with forecasting or nowcasting models of a monthly or quarterly variable: we are in the position of using 'big data' to learn

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about the relatively 'small data' of monthly economic aggregates.

The additional data that we consider pertain to Canadian debit and chequing transactions. These payments were constructed by aggregating the various payments that clear through the members of the Canadian Payments Association (CPA) on a daily basis. The payments data are organized by transactions between the various CPA members, and also by both type of payment and region; each monthly observation on debit or chequing transactions is computed by aggregating the information from approximately twenty business days per month, twenty member institutions in the payments system, fifteen different types of transaction, two directions of transaction (to or from an institution), and ten payment regions.

The literature on nowcasting has evolved rapidly over the last few years, although it has a long history, beginning with the work of Mitchell and Burns (1938), who classified hundreds of variables as leading, coincident and lagging indicators. This NBER-style study of indicators was updated regularly for the next thirty years, until interest waned around the 1970s. Stock and Watson (1989, 1991) subsequently renewed the interest in coincident indicators via the construction of simple indexes. More recent studies (e.g., Camacho & Perez-Quiros, 2008; Nunes, 2005) have focused on the construction of models primarily for very short-term forecasting, while others (e.g., Andreou, Ghysels, & Kourtellos, 2010) have focused on methodological contributions, with the aim of improving the incorporation of variables measured at different frequencies within a single model. A related strand of the literature aims to construct high-frequency indexes that are capable of capturing turning points in the business cycle in a timely manner (e.g., Aruoba, Diebold, & Scotti, 2009). Bańbura, Giannone, and Reichlin (2010) provide an up-to-date methodological overview, with an emphasis on the mixed frequencies of data and the 'ragged edge' property of data sets, in which components are released at different times.

The method that we use is related to that of Giannone, Reichlin, and Small (2008), in that we track improvements over time for nowcasts of GDP and retail sales growth for a given month. Specifically, we assess the marginal contribution of payments data at seven points in time over a two and a half-month period, extending from one month before the end of the month of interest to six weeks after it, or until two weeks before the data's eventual release. The prima facie evidence suggests that payments data, and especially debit card transactions, can often lower nowcast errors significantly.

The next section describes the payments system data that are being evaluated for their potential contributions to nowcasting, as well as the variables used in our baseline models (that is, models which omit the new payments system data) and the timing of data releases. Section 3 reviews the general challenges that are involved in the forecasting and nowcasting of GDP and retail sales growth, presents the models that are used for evaluating the marginal value of payments data for nowcasting, and measures these marginal contributions. The final section emphasizes some of the limitations of this study, and concludes.

2. Data and models

2.1. Payments data

Cashless means of payment have become progressively more popular throughout the developed economies. In the U.S., for example (Federal Reserve System, 2014a,b), debit cards are the fastest-growing non-cash means of payment, as cheque use has declined with a corresponding rapidity. The number (value) of debit card transactions per year grew by about 13.0% (12.5%) compounded annually over the period 2003–2012, vs. 5.1% (5.1%) compounded annually for credit cards. While cash transactions are not observed directly, ATM withdrawals fell slightly over the same period, although their average value did increase. The number of cheques written per year fell by approximately 6.2% compounded annually.[1] In Canada, the volume of cheque transactions for retail purchases has traditionally been low, but the pattern of a decline in the volume of cash transactions and an increase in the volumes of debit and credit card transactions is also observable.[2] Arango, Huynh, and Sabetti (2011) note that debit and credit cards accounted for about 89% of the value of retail transactions above $50 in Canada in 2009, while cash was used for the remaining 11%.[3] Debit card transactions in Canada are governed by the Interac Association, whose members are largely financial institutions, and clear through the Canadian Payments Association. In 2012, there were approximately 165 debit transactions per person in the U.S., and 126 per person in Canada (according to the Bank for International Settlements). The total value of all debit transactions in Canada reached $ 211 billion in 2014.

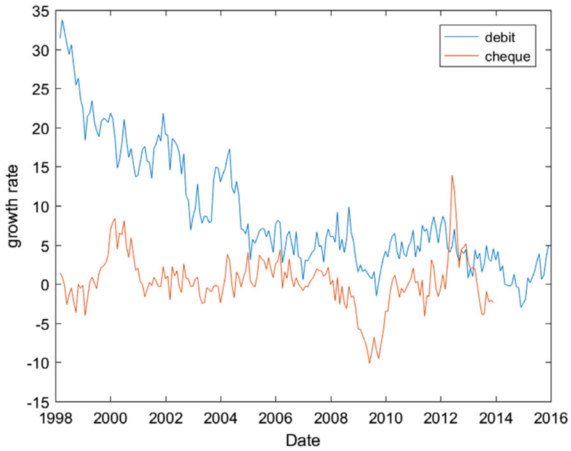
It is clear that both the number and proportion of consumer transactions that give rise to an observable electronic record are increasing. Such data have the potential to help us learn about consumer behaviour by examining these purchases both individually and at various levels of aggregation. One class of application, which generally relies on scanner data, has involved studying pricing decisions in an industrial organization context (see e.g., Campbell & Eden, 2014; Shankar & Bolton, 2004). Others have used scanner data to obtain an understanding of price movements or the effects of price movements on other purchases (e.g., Burstein, Eichenbaum, & Rebelo, 2005; Gicheva, Hastings, & Villas-Boas, 2010; Silver & Heravi, 2001). Another potential application is in studying the impacts of external events on consumer purchasing, as per Galbraith and Tkacz (2013), for example, who study consumer expenditures using the daily aggregate of all debit card expenditures at the times of three extreme events, and on the days following.

For the purposes of the present paper, however, we are interested in electronic transactions, because

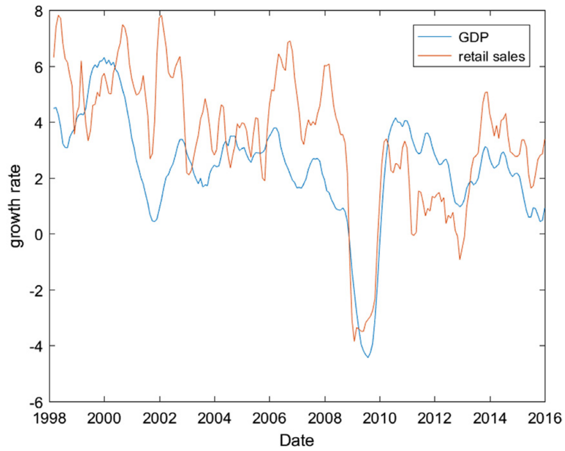
1 Federal Reserve System, 2014b, Table 3.4.2, p. 42.

2 See Arango, Huynh, Fung, and Stuber (2012, p. 32, Chart 1).

3 Cheques account for fewer than 1% of all transactions, but the average value of small (under $50,000) cheques that clear through the payments system is over $1,100, reflecting the fact that they are used for large infrequent transactions, such as rent payments, tuition fees, income and property taxes, and the purchase of expensive items such as automobiles.



(a) Cheque and debit payments.



(b) GDP and retail sales.

Fig. 1. Twelve-month growth rates, three-month moving average. For variable y at month t, the graphs depict $100\log[(y_t + y_{t-1} + y_{t-2})/(y_{t-12} + y_{t-13} + y_{t-14})]$.

consumption expenditure is a component of GDP, meaning that observing changes in consumption via payments system data provides an incomplete but direct source of information on changes in GDP. To the best of our knowledge, no study has yet used a broad range of payments system data to nowcast GDP growth for any country. However, researchers have begun to use aggregates of some high-volume electronically recorded data for various forecasting problems; see for example d'Amuri and Marcucci (2012), who find the Google index of internet job-search activity to have forecasting power for monthly U.S. unemployment, and Choi and Varian (2012), who consider nowcasting problems using Google search data.

As with individual Google searches, every transaction made on a debit or credit card is observable, in principle. To obtain a usable signal of economic activity, these data must be aggregated, in our case to the monthly frequency. Using different sources of debit data during a period of overlap, we are able to cross-check and verify the monthly aggregate provided by the CPA against the corresponding sum of daily aggregates provided by the Interac Association, and find that they match exactly. Daily or even higher-frequency data may be valuable in the study of the economic effects of transitory extreme events, as we have noted above; however, the monthly aggregate is the finest that we use for the present purpose.

The payments system variables available to us, aggregated to the monthly frequency from January 1997 to December 2015 (debit) or December 2013 (cheques), are as follows[4]:

- Debit: We measure point of sale (POS) payments that clear between two institutions. This involves a debit from the consumer's bank account and a credit to the merchant's account. This captures more than 80% of the approximately 4.5 billion (in 2013) annual debit transactions in the economy. We aggregate all debit transactions for the members of the Canadian Payments Association (CPA). We have data on the aggregate value and volume of all debit transactions.
- Cheques: As with debit cards, we capture all small cheques that clear betwen banks. We use the data on cheques valued under $50,000, as these would be used for payments of goods and services, whereas larger-valued cheques are typically used for financial transactions, which are less relevant for an analysis of GDP movements. These data were also obtained from the CPA.

Panel (a) of Fig. 1 plots the year-over-year growth rates of a quarterly moving average, computed as $\log[(y_t + y_{t-1} + y_{t-2})/(y_{t-12} + y_{t-13} + y_{t-14})]$, of the total monthly value transacted between 1998 and 2013 (2015) for cheques (debit cards), while panel (b) plots the analogously-defined growth rates of GDP and retail sales, for comparison. Although we see short-term noise fluctuations, we also see indications that these series are informative about economic activity, especially during downturns. The sample includes the 2008–09 recession, and all growth rates fall over that period. The milder downturn of 2001Q3 met the technical definition of a recession in the United States but saw only a single quarter of negative growth in Canada. Nonetheless, this period is visible in the debit card data.

Of course, an important caveat concerning these data is the fact that an overall increase or decrease in spending is not the only reason for payments rising or falling; they also change as consumers choose to switch between payments technologies. For example, a consumer choosing to switch from a debit card to a credit card for grocery purchases would result in a growth in credit card transactions and a fall in debit transactions. This means that, in

4 Over a shorter historical time period, we also obtained credit card transactions from the Canadian Bankers' Association, which aggregate Visa and MasterCard transactions to the monthly frequency; Visa and MasterCard account for about 90% of all Canadian credit card transactions. These data were analyzed in an earlier version of the present paper, ECB Statistics Series paper no. 10, August 2015. The results on this shorter sample suggested that much or all of the predictive power was captured by debit cards alone.

principle, using any series in isolation could lead to false signals about economic activity, whereas using all of them in a model together can endogenize a consumer's choice of payment technology. However, changes in the technologies used for consumer payments tend to be gradual, so that a single series may remain an adequate indicator of short-run changes in consumer expenditure.

A notable payments technology that is absent from our sample is cash. Although cash remains an important means of payment, withdrawals of cash may be used for purposes other than immediate consumer expenditure (for example, for precautionary purposes or for transfers among individuals), making it difficult to track accurately the cash component of any monetary aggregate that is being spent in a given period. In addition, cash is most often used for small transactions, meaning that cash purchases may be less highly correlated with aggregate spending fluctuations, which are influenced most by consumer spending decisions on larger discretionary items. Arango et al. (2011) note that debit and credit cards account for about 89% of the value of retail transactions above \$50, while cash is used for the remaining 11%; cash is used most widely for transactions under \$15, with 59% of the value of all such transactions being made using cash. In contrast, cheques are almost never used for retail purchases in Canada, although, as was mentioned above, they do capture some large, infrequent payments that could crowd out discretionary purchases made using debit and credit, and so are worth examining.

2.2. Nowcasting with payments data

Our aim is to evaluate the marginal usefulness, for nowcast accuracy, of payments system data. The potential for nowcast improvement from the use of payments data comes from their rapid availability, as has been noted, but also from the fact that they represent direct measurements of a component of GDP and retail sales. The national income identity is $Y = C + I + G + (X - M)$, in the standard notation where these symbols represent national income, consumption, investment, government expenditure, and net exports, respectively; consumption is the largest of the right-hand-side components (well over 50% of the total in Canada). The payments system data that we use measure a part of our quantities of interest directly, in contrast to studies that consider indirect indicators or proxies for the quantities of interest, such as search data.

We use the monthly GDP series that is now reported regularly by Statistics Canada; the reporting of the monthly GDP is relatively recent, and the actual time series of monthly GDP only goes back to 1997, but this is adequate for the present study, given the constraints imposed by the availability of payments system data. The quarterly GDP is simply the average of the monthly GDP measured within the quarter, and is still reported four times per year. It is released with the full set of national accounts, but the other GDP components (C, I, G, X, M) are not released on a monthly basis. However, retail sales are released on a monthly basis, and we nowcast this variable as well.

The question of whether the signal from payments data is strong enough to provide additional forecasting power remains to be investigated; we evaluate whether these data provide any new information at the margin through comparisons with standard forecasting or nowcasting models that can be computed using the usual macroeconomic data provided by statistical agencies. The standard models form our base-case indicators, and we test for nowcast loss reductions in models with payments data added to the set of explanatory variables. The former models are nested within the latter, so that the asymptotic variance of a scaled loss difference is zero under the null that the additional variables have no predictive ability, and a required condition for asymptotic normality of standard test statistics fails. We therefore use the tests and critical values of McCracken (2007) that are designed for this case.

2.3. Base-case indicators

Although a visual inspection of Fig. 1, as well as *a priori* arguments, suggest that payments variables may be correlated with the business cycle, we need to assess the information content of these variables relative to indicators that are already compiled and monitored regularly. We do this by using lags of the variables of interest, GDP growth and retail sales growth, together with the CPI (since we are nowcasting using nominal quantities) and the unemployment rate.[5] The overall unemployment rate incorporates the impact of public sector hiring, and has sometimes been found to have marginally useful information content for GDP growth. It is also released relatively quickly, with the unemployment rate for month t being released around the second week of month $t + 1$.

We nowcast k-month growth rates of GDP and retail sales, that is $\log(y_t/y_{t-k})$; when using the indicator variables in our nowcasting equations, we convert them into growth rates of the corresponding order, which also induces (approximate) stationarity.

The remainder of this study is concerned with whether payments variables contain any relevant information that is not already captured by the unemployment rate, CPI and the dynamics of the variable being nowcast itself. To be able to make this assessment, we need to ensure that the models incorporate only information that is available at the time when a nowcast is made. In the next section, we explain how we update our models over time, and what data are available at each date.

2.4. Timing of data releases

From the discussion above, we can write

$$\dot{y} = f(\dot{y}_{-i}, \dot{p}, \Delta u, Z), \tag{1}$$

where $\dot{y}$ and $\dot{y}_{-i}$ are the GDP growth or retail sales growth and lags, $\dot{p}$ is the growth rate of the CPI, Δu is the change in

5 Earlier versions of this paper used Statistics Canada's Composite Leading Indicator, but this indicator was discontinued after the release of 23 May, 2012. In addition, some of the components within the CLI were measured with a lag, as they relied on survey data. This was the case for the retail trade variables in particular, as well as new orders of durables and shipments/inventories of finished goods in the manufacturing group; for the CLI of a given month t, the data for these components actually reflect observations for month $t - 2$.

Table 1
Nowcast dates and the corresponding data availability.

Variable	Date at which nowcast is performed						
	(1) First day of month t	(2) First day of month $t+1$	(3) 15th day of month $t+1$	(4) 22nd day of month $t+1$	(5) First day of month $t+2$	(6) 15th day of month $t+2$	(7) 22nd day of month $t+2$
	Latest observation available at date of nowcast						
GDP or retail sales	$t-3$	$t-2$	$t-2$	$t-2$	$t-1$	$t-1$	$t-1$
Unemployment	$t-2$	$t-1$	t	t	t	$t+1$	$t+1$
CPI	$t-2$	$t-1$	$t-1$	t	t	t	$t+1$
Debit	$t-1$	t	t	t	$t+1$	$t+1$	$t+1$
Cheques	$t-1$	t	t	t	$t+1$	$t+1$	$t+1$
	Example of nowcast dates, for March as month t						
Variable	Date at which nowcast is performed						
	(1) March 1	(2) April 1	(3) April 15	(4) April 22	(5) May 1	(6) May 15	(7) May 22
	Latest observation available at date of nowcast						
GDP or retail sales	December	January	January	January	February	February	February
Unemployment	January	February	March	March	March	April	April
CPI	January	February	February	March	March	March	April
Debit	February	March	March	March	April	April	April
Cheques	February	March	March	March	April	April	April

the unemployment rate, and Z is a vector of growth rates of payments variables, which may include the value and volume of debit and chequing transactions.

The growth rates are computed for several horizons: one, three and twelve months ($k = 1, 3, 12$). The base-case models omit the payments variables, and a number of alternative models are reported below which incorporate functions of cheque and debit transaction data.

We have omitted time subscripts from Eq. (1), as these will vary according to the precise time at which an analyst is required to generate a nowcast. However, we need to specify the appropriate datings for estimation and nowcasting purposes. In what follows, we assume that one is required to generate a nowcast of $\dot{y}$ for month t, with the first nowcast being generated on the first day of the given month, and new nowcasts being generated at several subsequent dates until the official measurement for the month is released. In total, we produce nowcasts on seven dates, with the fifth one being made two months after the first day of the month of interest (i.e., one month and one day after the close of month t), and the seventh and last being made three weeks after the beginning of month $t + 2$. Table 1 gives the dates of the nowcasts and the latest data available, for a given month t. The second part of the table uses the example of the month of March, for which official data on GDP and retail sales are released at approximately the end of May (the release lag is approximately two months, for both the monthly and quarterly GDP). We produce nowcasts as of the first day of March and on six more dates through to the third week of May. Table 1 gives this example in detail, together with the latest availability dates for the data being used in the nowcast.

Given the release dates above, we can specify the seven variants of Eq. (1) that an analyst can estimate for each of the seven different nowcasting points for a given month t. Note again that while the release dates for GDP, retail sales, CPI and the unemployment rate are regular and known in advance, payments data are recorded electronically and are aggregated at a daily frequency, and in principle can be released the next business day.

2.5. *Model specification*

In each case, the nowcast specifications used here are linear models in which the growth rate of the target variable is projected onto data that are observable at the time when the relevant nowcasting is performed, corresponding to Table 1.

A general form of the specification is:

$$\dot{y} = \beta_0 + \beta(L)\dot{y} + \gamma_1(\Delta u_{t-i}) + \gamma_2(\dot{p}_{t-i}) + \nu_1\dot{D}_{t-i} + \nu_2\dot{Q}^D_{t-i} + \nu_3\dot{C}_{t-i} + \nu_4\dot{Q}^C_{t-i} + \epsilon_t, \tag{2}$$

where y is the target variable (GDP or retail sales), $\beta(L)$ is a lag polynomial, Δu is the change in the unemployment rate, p is the consumer price index, D and Q^D are the value and number of debit transactions, C and Q^C are the value and number of cheque transactions, and a 'dot' superscript denotes a growth rate over a period of k months, $k = 1, 3, 12$. The models on the sample to the end of 2013 include all of these payments variables, while those on the sample to the end of 2015 include $\dot{D}$ and $\dot{Q}^D$ but not the cheque variables.

The base case models are nested within this specification, and represent the model with the best forecasting performance achieved without the use of the payments variables. We consider up to 12 lags for the dependent variables, with the final choice being made based on minimizing the Schwarz criterion. For $k = 1$ we have three lags; for $k = 3$ we have four lags; and for $k = 12$ we have seven lags. Of course, only the lagged values that would be available at the time of the nowcast are used in the specification for each date. Although only one lag of the payments variables is shown above, we include both payments observations t and $t + 1$ for the later nowcasts (numbered 5–7), for which they would be available.

3. Nowcasting GDP and retail sales growth

We now make an empirical examination of the usefulness of the payments data, with the aim of nowcasting the (nominal) GDP and retail sales growth. The former is one of the most important series in macroeconomics, while the latter is a series that is often followed as a monitor of the consumer sector, and is particularly interesting for our present purpose because of the link to debit payments, by which retail purchases are often made.

The problem of forecasting the change in GDP is one of the most challenging in macroeconomics. Measurements are subject to substantial revisions, often many years after the observations, and even first releases arrive with a substantial lag. Moreover, the autocorrelations of the series are low, so that the standard time series methods for exploiting dynamic patterns have little power; more than one quarter into the future, models show forecast RMSEs that are barely lower than the unconditional variance of the series, if at all: that is, models often do not improve on simply using the unconditional mean of the series as its forecast (see for example Galbraith, 2003; Galbraith & Tkacz, 2007).

In addition, there are various different measurements of (either real or nominal) GDP growth in which an analyst might be interested, primarily along the dimensions of vintage and time span. One can consider predictive power for both first-release and latest-vintage data, at the quarterly and annual aggregations. First-release data are of particular interest to forecasters who will be evaluated in the short term with regard to the accuracy of their forecasts, and good forecasts of first-release numbers enhance the credibility of policymakers. From the point of view of the choice of the most appropriate policy at a given time, however, the forecast accuracy relative to the best (presumably latest-vintage) estimate of GDP is the relevant criterion. The present study uses latest-vintage data throughout, reflecting in part the lack of a consistent series of vintage Canadian GDP data.[6]

We compute results on two spans of data and for one-, three- and 12-month growth rates. The shorter span, from January 2008 through to the end of 2013, contains the larger selection of payments variables, with the total values and numbers of transactions for both debit payments and cheques. The longer sample extends for 24 more months, through to the end of 2015, but uses debit card payments data alone. From January 2014, our data source does not maintain the division of cheque transactions into smaller cheques of less than \$50,000, and larger cheques exceeding that value. The precise definitions of all data series used are provided in the Appendix. Because the variables that we forecast are seasonally adjusted, we adjust the raw payments data using an exponential smoother (see e.g., Gardner, 1985).

The empirical results are recorded in four tables. Tables 2 and 3 use data through to the end of 2015 on debit payments, for GDP and retail sales respectively. Tables 4 and 5 use data through to the end of 2013 only, but include both debit and cheque payment data.

Our nowcasting exercise uses the first 108 observations for the initial estimation of our parameters, which are used to produce a nowcast for January 2007. The sample is then updated monthly and the parameters are re-estimated recursively, producing nowcasts through to the end of either 2013 or 2015. The sample sizes used for the initial estimation and nowcast evaluation are given in the notes to each table. We track not only the marginal value of the payments variables, but also the evolution of the nowcasting performance over the seven dates on which nowcasts are performed, as additional data become available. In each case, the forecasting models without payments variables are nested within the larger models in which the payments variables are present. The base-case model that is used for each value of k and nowcast date is that which achieves the lowest RMSE using traditional variables, and is highlighted in the tables below. We then test for the equality of MSEs for nested models. Under the null hypothesis, the RMSEs of the base-case model and of the model augmented with payments variables are equal; under the alternative, the RMSE of the payments-augmented model is lower. We perform the recursive OOS-t test of McCracken (2007), with asymptotic critical values taken from Table 1 of that paper.[7]

In interpreting the tables, we pay particular attention to the marginal contribution of payments data, if any, but also to the degree to which the estimated nowcast errors fall as information accumulates over the two month and three week span of the nowcast interval.

We summarize our interpretation as follows.

- On the longer sample, the addition of debit data to the base case models (see case (c), Tables 2 and 3) generally produces statistically significant reductions in nowcast losses for GDP growth and retail sales growth at most nowcast dates and for each of the growth rates (one, three and 12 months). The same qualitative pattern appears on the shorter sample (case (c), Tables 4 and 5), although the statistical significance is lost for GDP one-month growth forecasts ($k = 1$) and nowcasts beyond the second (these $k = 1$, nowcast 3–7 results were also relatively weak on the larger sample in Table 2).
- The estimated magnitudes of the loss reductions are comparable for the two series, GDP and retail sales, although they are slightly larger on average for retail sales (comparing case (c) in Tables 2 and 3).

6 Vintage data on real GDP in chained 2007 dollars are available via archived versions of the Statistics Canada catalogue 15-001X, produced through to December 2012 (October 2012 monthly GDP estimate). Vintage data reported on a comparable basis are not currently available thereafter. Statistics Canada's quarterly GDP system is consistent with its monthly GDP series, in the sense that the former is the quarterly average of the latter. Although Statistics Canada only releases the full National Accounts variables (C, I, G, X, M) quarterly, a seasonally-adjusted GDP estimate is made available at the monthly frequency, and it is this series that we use here.

7 The critical values depend upon the number of additional variables in the larger of the two nested models (k_2 in the notation of (McCracken, 2007) and on the ratio $\pi = P/R$ of the forecast sample size to the initial estimation sample size. The optimal number of lags for the dependent variable was estimated by minimizing the Schwarz criterion.

Table 2
Root mean squared nowcast errors, GDP growth, SA (base models (shaded) and models with debit).

Nowcast:	1	2	3	4	5	6	7
	RMSE (k = 1)						
(a) Lagged (3 lags) GDP	***4.153***	4.037	4.037	4.037	4.172	4.172	4.172
(b) Lagged (3 lags) GDP, Unemployment & Inflation	4.176	***3.936***	***3.741***	***3.686***	***3.847***	***3.798***	***3.803***
(c) Basecase & Debit	4.075 [0.979**]	3.844 [0.741**]	3.693 [0.454*]	3.646 [0.394*]	3.791 [0.539**]	3.753 [0.413*]	3.765 [0.346*]
	RMSE (k = 3)						
(a) Lagged (4 lags) GDP	3.037	2.397	2.397	2.397	1.593	1.593	1.593
(b) Lagged (4 lags) GDP, Unemployment & Inflation	***2.889***	***2.193***	***1.986***	***1.929***	***1.427***	***1.380***	***1.383***
(c) Basecase & Debit	2.755 [1.188**]	2.074 [1.293**]	1.857 [1.407***]	1.812 [1.308**]	1.399 [0.486*]	1.361 [0.347*]	1.367 [0.281*]
	RMSE (k = 12)						
(a) Lagged (7 lags) GDP	***1.023***	***0.773***	0.773	0.773	***0.508***	0.508	0.508
(b) Lagged (7 lags) GDP, Unemployment & Inflation	1.065	0.803	***0.742***	***0.732***	0.515	***0.488***	***0.489***
(c) Basecase & Debit	0.996 [1.386***]	0.767 [0.392*]	0.635 [3.596***]	0.624 [3.548***]	0.532 [-0.812]	0.457 [1.528***]	0.458 [1.514***]

Notes: The initial sample is January 1998–December 2006 ($R = 108$ observations), and the nowcast period is January 2007–December 2015 ($P = 108$ observations); $k = 1, 3, 12$ for a k-month growth rate. McCracken's (2007) recursive OOS-t test statistics are given in brackets.
In this table, $\pi = 1$ and we augment the base-case model with the value and volume of debit transactions. For nowcasts 1–4, we only include the latest observation of value and volume (see Table 1 for the timing: we have the value and volume of debit at either t or $t-1$), so the alternative model has $k_2 = 2$ extra parameters. For nowcasts 5–7, we include the $t+1$ observation of debit value and volume in addition to the time t observations, so the alternative model has $k_2 = 4$ additional parameters, on value(t), volume(t), value($t+1$), and volume($t+1$). From Table 1 of McCracken (2007), the critical values for $k_2 = 2$ and $\pi = 1$ are (1%, 5%, 10% respectively) 1.312, 0.704, 0.361. For $k_2 = 4$ and $\pi = 1$, the critical values are 1.119, 0.502, 0.169.
*** denotes rejection of the null hypothesis at the 1% significance level; ** denotes rejection at the 5% significance level; and * denotes rejection at the 10% significance level.

- In the sample to the end of 2013 for which we have data on small cheque transactions (Tables 4 and 5), we observe that the cheque transaction data do show some statistically significant value for earlier GDP nowcasts in models without debit data (Table 4, case (d), $k = 3, 12$, nowcasts 1–4), but make very little or no estimated additional contribution to GDP nowcasting when debit data are present in the model (Table 4, comparing cases (e) and (c)).
- For retail sales growth, cheque data produce no discernible benefit in nowcast reduction, even in the absence of debit data in the model, with the exception of a few early nowcasts of 12-month growth rates (Table 5, case (d)). When debit data are included in the retail sales model (Table 5, comparing cases (e) and (c)), nowcast performances deteriorate with the addition of cheque data, which is consistent with the hypothesis that these data have no marginal value when debit data are present, so that we are merely adding noise to the regression model. These results are also consistent with the low usage of cheques for consumer purchases.
- As information accrues between the first and last nowcasts, the nowcast loss for GDP typically falls by roughly 10% for one-month growth rates, and around 50% for the less noisy three- and 12-month growth rates (Table 2, case (c), comparing nowcasts 1 and 7). For retail sales, the reductions in nowcast losses over the interval are much smaller: only a few percent for one-month growth, approximately 10%–15% for three-month growth, and approximately 1/3 for 12-month growth (Table 3, case (c), comparing nowcasts 1 and 7).

Globally, the results suggest that data on debit payments have useful and statistically significant value in reducing nowcast losses for these variables. Data on small cheque transaction values appear to be of negligible additional value given debit card data.

Table 3
Root mean squared nowcast errors, retail sales growth, SA (base models (shaded) and models with debit).

Nowcast:	1	2	3	4	5	6	7
	RMSE (k = 1)						
(a) Lagged (3 lags) Retail Sales	11.467	***11.508***	***11.508***	***11.508***	***11.450***	***11.450***	***11.450***
(b) Lagged (3 lags) Retail Sales, Unemployment & Inflation	***11.423***	11.837	11.539	11.669	11.701	11.901	11.672
(c) Basecase & Debit	11.548 [-1.275]	11.277 [1.181**]	11.277 [1.181**]	11.277 [1.181**]	11.207 [0.892**]	11.207 [0.892**]	11.207 [0.892**]
	RMSE (k = 3)						
(a) Lagged (3 lags) Retail Sales	***5.934***	***5.566***	***5.566***	***5.566***	***4.868***	***4.868***	***4.868***
(b) Lagged (3 lags) Retail Sales, Unemployment & Inflation	5.992	5.792	5.818	5.934	5.146	5.282	5.333
(c) Basecase & Debit	5.628 [2.066***]	5.203 [2.487***]	5.203 [2.487***]	5.203 [2.487***]	4.632 [1.978***]	4.632 [1.978***]	4.632 [1.978***]
	RMSE (k = 12)						
(a) Lagged (7 lags) Retail Sales	2.147	***1.846***	***1.846***	***1.846***	***1.454***	***1.454***	***1.454***
(b) Lagged (7 lags) Retail Sales, Unemployment & Inflation	***2.133***	1.869	1.867	1.876	1.475	1.516	1.498
(c) Basecase & Debit	2.081 [2.194***]	1.817 [1.425***]	1.817 [1.425***]	1.817 [1.425***]	1.458 [-0.142]	1.458 [-0.142]	1.458 [-0.142]

Notes: The initial sample is January 1998 to December 2006 ($R = 108$ observations), and the nowcast period is January 2007 to December 2015 ($P = 108$ observations); $k = 1, 3, 12$ for a k-month growth rate. McCracken's (2007) recursive OOS-t test statistics are given in brackets. For the critical values used, see the notes to Table 2.
*** denotes rejection of the null hypothesis at the 1% significance level; ** denotes rejection at the 5% significance level; and * denotes rejection at the 10% significance level.

4. Conclusion

Nowcasts are important for many decision-makers, given the substantial time lag between the end of a period and the appearance of official data for many macroeconomic aggregates. The present study has assessed how payments-system data, which are recorded electronically and, in principle, are available very quickly, can contribute to the production of more accurate nowcasts.

We evaluate nowcast loss (RMSE) reductions for a number of different growth rates (one, three, and twelve months) and for seven dates within the nowcast period, from the opening day of the month of interest until three weeks after the close of the next month, beyond which point the official estimate soon becomes available. A number of these results are statistically significant based on the tests of McCracken (2007). In particular, the empirical results suggest that both debit card transactions and, to a lesser extent, cheque transactions can help to reduce nowcast errors for GDP, and that debit card data can do so for retail sales as well. We note again that data on the value of transactions completed by cheque has little if any useful power for nowcasting retail sales, a result that is consistent with the fact that few retail transactions now take place by cheque. Even for GDP nowcasting, debit data alone produce all or virtually all of the improvements in nowcast accuracy. Globally, in addition to very low error rates and a very rapid availability, these data appear to have genuine value in reducing the short-term uncertainty about important macroeconomic variables. It seems reasonable to suppose that the daily availability to policymakers of information on the value of debit transactions, which is well within the range of technical feasibility, could provide noteworthy improvements in the quality of economic monitoring.

Of course, there are numerous remaining avenues through which one could continue to investigate the usefulness of payments-system data and the optimal form in which to incorporate this information into nowcasting and forecasting models, bearing in mind that, in principle, policymakers could retrieve such data on the day following the day being measured. One further potentially fruitful development of this research would therefore be to combine electronic transactions with other data that can be measured with some accuracy at a daily frequency, and to establish a framework that would

Table 4
Root mean squared nowcast errors, GDP growth, SA (base models (shaded) and models with debit and cheques).

Nowcast:	1	2	3	4	5	6	7
	RMSE (k = 1)						
(a) Lagged (3 lags) GDP	***4.317***	4.116	4.116	4.116	4.293	4.293	4.293
(b) Lagged (3 lags) GDP, Unemployment & Inflation	4.358	***4.080***	***3.800***	***3.739***	***3.931***	***3.857***	***3.858***
(c) Basecase & Debit	4.231 [0.929**]	4.001 [0.538*]	3.775 [0.202]	3.722 [0.141]	3.895 [0.307*]	3.838 [0.159]	3.844 [0.108]
(d) Basecase & Cheques	4.388 [-1.205]	4.097 [-0.101]	3.907 [-0.671]	3.857 [-0.760]	4.386 [-1.227]	4.301 [-1.195]	4.328 [-1.196]
(e) Basecase, Debit & Cheques	4.330 [-0.098]	4.112 [-0.164]	3.916 [-0.677]	3.866 [-0.758]	4.318 [-1.294]	4.250 [-1.287]	4.281 [-1.300]
	RMSE (k = 3)						
(a) Lagged (4 lags) GDP	3.172	2.430	2.430	2.430	1.629	1.629	1.629
(b) Lagged (4 lags) GDP, Unemployment & Inflation	***3.077***	***2.293***	***2.041***	***1.976***	***1.475***	***1.403***	***1.405***
(c) Basecase & Debit	2.966 [0.841**]	2.181 [1.032**]	1.924 [1.081**]	1.871 [1.004**]	1.466 [0.128]	1.411 [-0.119]	1.416 [-0.159]
(d) Basecase & Cheques	3.014 [0.887**]	2.144 [1.599***]	1.903 [1.603***]	1.851 [1.511***]	1.702 [-0.967]	1.583 [-0.958]	1.600 [-0.951]
(e) Basecase, Debit & Cheques	2.954 [0.818**]	2.114 [1.283***]	1.869 [1.267***]	1.824 [1.179**]	1.712 [-0.894]	1.608 [-0.924]	1.633 [-0.926]
	RMSE (k = 12)						
(a) Lagged (7 lags) GDP	***1.053***	***0.781***	0.781	0.781	***0.514***	0.514	0.514
(b) Lagged (7 lags) GDP, Unemployment & Inflation	1.093	0.816	***0.744***	***0.736***	0.523	***0.487***	***0.488***
(c) Basecase & Debit	1.027 [1.126**]	0.778 [0.180]	0.636 [3.466***]	0.625 (3.395***)	0.511 [0.172]	0.450 [1.709***]	0.451 [1.658***]
(d) Basecase & Cheques	1.036 [0.646*]	0.753 [1.192**]	0.672 [2.557***]	0.667 (2.453***)	0.521 [-0.317]	0.493 [-0.226]	0.494 [-0.231]
(e) Basecase, Debit & Cheques	1.024 [0.804**]	0.759 [0.766**]	0.625 [2.854***]	0.619 (2.766***)	0.558 [-0.819]	0.506 [-0.377]	0.507 [-0.372]

Notes: The initial sample is January 1998 to December 2006 ($R = 108$ observations), and the nowcast period is January 2007 to December 2013 ($P = 84$ observations); $k = 1, 3, 12$ for a k-month growth rate. McCracken's (2007) recursive OOS-t test statistics are given in brackets.
This table also considers cheques (for which data are only available until the end of 2013); we have three alternative models:
(c) Base case + value and volume of debit;
(d) Base case + value and volume of cheques;
(e) Base case + value and volume of debit + value and volume of cheques.
For (c) and (d), we still have $k_2 = 2$ for nowcasts 1–4, but $k_2 = 4$ for nowcasts 5–7. For (e), we have $k_2 = 4$ for nowcasts 1–4, but $k_2 = 8$ for nowcasts 5–7. With a shorter out-of-sample period, we now have $\pi = 0.778$. Interpolating linearly, the 1%, 5% and 10% critical values are as follows:

- for (c) and (d), nowcasts 1–4, $k_2 = 2$, $\pi = 0.778$: 1.392, 0.792, 0.465;
- for (c) and (d), nowcasts 5–7, and (e), nowcasts 1–4, $k_2 = 4$, $\pi = 0.778$: 1.214, 0.627, 0.280;
- for (e), nowcasts 5–7, $k_2 = 8$, $\pi = 0.778$: 0.902, 0.320, 0.018.

*** denotes rejection of the null hypothesis at the 1% significance level; ** denotes rejection at the 5% significance level; and * denotes rejection at the 10% significance level.

automate the generation of nowcasts on a daily basis as new data are observed. In this context, we can also anticipate more effective methods for combining data at different frequencies within a single model. The state space approach used by Armah (2011) could be one avenue through which this could be pursued, as could a MIDAS mixed-frequency regression approach (e.g., Andreou et al., 2010; Duarte, Rodrigues, & Rua, in press).

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Appendix. Data sources

Gross Domestic Product (GDP): nominal, millions of current dollars, monthly, seasonally adjusted at annual rates. Based on North American Industry Classification System (NAICS) 2007. Source: Statistics Canada; series V65201210, CANSIM table 379-0031. Dates: Jan. 1997–Dec. 2015. Release date: approximately two months after the end of the month being measured.

Retail sales: nominal, millions of current dollars, monthly, seasonally adjusted at annual rates. Source:

Table 5
Root mean squared nowcast errors, retail sales growth, SA (base models (shaded) and models with debit and cheques).

Nowcast:	1	2	3	4	5	6	7
	RMSE (k = 1)						
(a) Lagged (3 lags) Retail Sales	11.988	***12.040***	12.040	12.040	***12.102***	***12.102***	***12.102***
(b) Lagged (3 lags) Retail Sales, Unemployment & Inflation	***11.882***	12.426	***12.000***	***12.020***	12.222	12.475	12.144
(c) Basecase & Debit	12.047 [-1.408]	11.802 [1.189**]	11.923 [0.437]	11.771 [1.278**]	11.881 [0.730**]	11.881 [0.730**]	11.881 [0.730**]
(d) Basecase & Cheques	12.423 [-2.291]	12.167 [-1.169]	12.152 [-1.370]	12.131 [-1.230]	12.429 [-1.281]	12.429 [-1.281]	12.429 [-1.281]
(e) Basecase, Debit & Cheques	12.471 [-2.420]	11.902 [0.669**]	12.014 [-0.072]	11.834 [0.929**]	12.256 [-0.488]	12.256 [-0.488]	12.256 [-0.488]
	RMSE (k = 3)						
(a) Lagged (3 lags) Retail Sales	***6.475***	***6.040***	***6.040***	***6.040***	***5.265***	***5.265***	***5.265***
(b) Lagged (3 lags) Retail Sales, Unemployment & Inflation	6.530	6.310	6.323	6.441	5.563	5.727	5.784
(c) Basecase & Debit	6.078 [2.498***]	5.603 [2.820***]	5.603 [2.820***]	5.603 [2.820***]	4.960 [2.460***]	4.960 [2.460***]	4.960 [2.460***]
(d) Basecase & Cheques	6.466 [0.257]	6.021 [0.239]	6.021 [0.239]	6.021 [0.239]	5.446 [-0.733]	5.446 [-0.733]	5.446 [-0.733]
(e) Basecase, Debit & Cheques	6.152 [2.361***]	5.660 [2.566***]	5.660 [2.566***]	5.660 [2.566***]	5.165 [0.620**]	5.165 [0.620**]	5.165 [0.620**]
	RMSE (k = 12)						
(a) Lagged (4 lags) Retail Sales	2.366	***2.022***	***2.022***	***2.022***	***1.568***	***1.568***	***1.568***
(b) Lagged (4 lags) Retail Sales, Unemployment & Inflation	***2.347***	2.045	2.040	2.051	1.587	1.636	1.610
(c) Basecase & Debit	2.295 [2.090***]	1.991 [1.484***]	1.991 [1.484***]	1.991 [1.484***]	1.543 [0.860**]	1.543 [0.860**]	1.543 [0.860**]
(d) Basecase & Cheques	2.318 [1.104**]	1.992 [0.623*]	1.992 [0.623*]	1.992 [0.623*]	1.611 [-0.655]	1.611 [-0.655]	1.611 [-0.655]
(e) Basecase, Debit & Cheques	2.306 [1.238***]	1.994 [0.53*]	1.994 [0.573*]	1.994 [0.573*]	1.590 [-0.347]	1.590 [-0.347]	1.590 [-0.347]

Notes: See the notes to Table 4.

Statistics Canada; series V65201368, CANSIM table 379-0031. Dates: Jan. 1997–Dec. 2015. Release date: approximately two months after the end of the month being measured.

Unemployment: Canada, population 15 and over, both sexes, seasonally adjusted, monthly. Source: Statistics Canada; series V2062815, CANSIM table 282-0087. Dates: Jan. 1976–Dec. 2015. Release date: approximately two weeks after the end of the month being measured.

Consumer Price Index: Canada, all items, seasonally adjusted, monthly, 2002 = 100. Source: Statistics Canada; series V41690914. CANSIM table 326-0022. Dates: Jan. 1992–Dec. 2015. Release date: approximately three weeks after the end of the month being measured.

Debit card purchases: point of service, value (current dollars), not seasonally adjusted, daily; point of service, volume (number of transactions), not seasonally adjusted, daily. Source: Canadian Payments Association, Ottawa. Dates: Jan. 1997–Dec. 2015. Availability date: daily data, next business day; monthly data, first day of the following month.

Cheques: cheques under $50,000 encoded by direct clearers, value (current dollars), not seasonally adjusted, daily; cheques under $50,000 encoded by direct clearers, volume (number of transactions), not seasonally adjusted, daily. Source: Canadian Payments Association, Ottawa. Dates: Jan. 1997–Dec. 2013. Availability date: daily data, next business day; monthly data, first day of the following month.

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