EUROPEAN CENTRAL BANK
EUROSYSTEM

Statistics Paper Series

John W. Galbraith
and Greg Tkacz

Nowcasting GDP with electronic payments data

No 10 / August 2015

Contents

Abstract

We assess the usefulness of a large set of electronic payments data comprising debit and credit card transactions, as well as cheques that clear through the banking system, as potential indicators of current GDP growth. These variables capture a broad range of spending activity and are available on a very timely basis, making them suitable current indicators. While every transaction made with these payment mechanisms is in principle observable, the data are aggregated for macroeconomic forecasting. Controlling for the release dates of each of a set of indicators, we generated nowcasts of GDP growth for a given quarter over a span of five months, which is the period over which interest in nowcasts would exist. We find that nowcast errors fall by about 65 per cent between the first and final nowcast. Evidence on the value of the additional payments variables suggests that there may be modest reductions in forecast loss, tending to appear in nowcasts produced at the beginning of a quarter. Among the payments variables considered, debit card transactions appear to produce the greatest improvements in forecast accuracy.

Keywords: electronic payments; GDP; nowcasting; vintage data

JEL codes: E32, E37, C53

1 Introduction

Observing the current pace of economic activity is crucial to policy-makers and other decision makers as it can affect, for example, the implementation of countercyclical policies or near-term production decisions. However, the most important measure of economic activity – 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 in order to monitor economic conditions.

The main contribution of the present study to this problem is in investigating a broadening of the information set at the disposal of nowcasters. We compile and examine the marginal utility of, a database on the transactions passing through the payments system, providing us with information on the values and volumes of debit and credit card transactions, as well as of cheques that clear through the banking system. Apart from 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. All such electronic payments are in principle observable to the investigator; however there are, for example, more than 12 million debit transactions per day in Canada. For use with forecasting or nowcasting models of a quarterly variable, a high degree of aggregation is therefore necessary: we are in the position of using ‘big data’ to learn about the ‘small data’ of quarterly GDP growth.

The data that we consider pertain to Canadian debit, credit and chequing transactions. Debit and chequing payments were constructed by aggregating the various payments that clear through the members of the Canadian Payments Association (CPA) on a daily basis. With the payments data being organised by transactions between the various CPA members, and also by type of payment and by region, each monthly observation on debit or chequing transactions can be computed by aggregating the information in a 120,000-row matrix. Credit card transactions were obtained from the Canadian Bankers’ Association, which aggregates Visa and MasterCard transactions to the monthly frequency.[1]

The literature on nowcasting has evolved rapidly in 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 regularly updated for the next thirty years, until interest waned around the 1970s. Stock and Watson (1989, 1991) subsequently renewed interest in coincident indicators via the construction of simple indexes. More recent studies (e.g. Nunes 2005, Camacho and Perez-Quiros 2008) have focused on the construction of models primarily for very short-term forecasting, while others (e.g. Andreou, Ghysels and Kourtellos 2010) have focused on methodological contributions aimed at

[1] Visa and MasterCard account for about 90% of all Canadian credit card transactions.

improving the incorporation of variables measured at different frequencies within a single model. A related strand of literature aims at constructing high-frequency indexes capable of capturing turning points in the business cycle in a timely manner (e.g. Aruoba, Diebold and Scotti 2009). Bańbura et al (2010) provide an up-to-date methodological overview, emphasising 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 GDP nowcast improvements for a given quarter over time. Specifically, we assess the marginal contribution of payments data over a five-month span, which extends from the first day of a quarter until the month of the data's eventual release. The prima facie evidence suggests that payments data, especially debit card transactions, typically lower nowcast errors. However, the degree of reduction is difficult to estimate precisely in the small sample sizes inevitable in dealing with quarterly GDP data.

In the next section we describe the payments system data that are being evaluated for their potential contribution to nowcasting, as well as the variables used in our base-case model, and describe the timing of data releases. Section 3 reviews the general challenges involved in forecasting and nowcasting GDP growth, presents the model used for evaluation of the marginal value of payments data for GDP nowcasting, and measures these marginal contributions. The final section emphasises some limitations of this study, and concludes.

2 Data

2.1 Payments data

Cashless means of payment have become progressively more popular throughout the developed economies. In the U.S. (Federal Reserve System 2014), debit cards have been the fastest growing non-cash means of payment, as cheque use has declined with corresponding rapidity. The number (value) of debit card transactions 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 directly observed, ATM withdrawals fell slightly over the same period, although their average value did increase. The number of cheques written fell by approximately 6.2% compounded annually.[2] In Canada, the volume of cheque transactions for retail purchases has traditionally been low, but the pattern of decline in the volume of cash transactions and increase in the volume of debit and credit card transactions is also observable.[3] Arango et al. (2011) note that in 2009, debit and credit cards accounted for about 89% of the value of retail transactions above $50 in Canada, while cash is used for the remaining 11%.[4] In 2012, there were approximately 165 debit transactions per person in the U.S., and 126 per person in Canada.[5]

Clearly the number and proportion of consumer transactions giving rise to an observable electronic record is increasing, and such data offer the potential to help us learn about consumer behaviour by examining these purchases both individually and at various aggregations. One class of application, generally relying on scanner data, has been to study pricing decisions in an industrial organization context (see e.g. Campbell and Eden 2014. Shankar and Bolton 2004). Others have used scanner data to understand price movements or the effects of price movements on other purchases (e.g. Silver and Heravi 2001, Burstein et al. 2005, Gicheva et al. 2010). Another potential application is in studying the impact of external events on consumer purchasing, as in for example Galbraith and Tkacz (2013), 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 consumption expenditure is a component of GDP, so that observing changes in consumption via payments system data provides an incomplete but direct source of information on changes in GDP. To our knowledge, a study using a broad range of payments system data to nowcast GDP growth has not yet been undertaken for any country. However, researchers are beginning to use

---

2 Federal Reserve System 2014, Summary Report, Table 3.4.2, p. 42.

3 Arango et al. (2012), p. 32, Chart 1.

4 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, or the purchase of expensive items such as automobiles.

5 Bank for International Settlements.

aggregates of some high-volume electronically recorded data for some forecasting problems; see for example d'Amuri and Marcucci (2012) who use the Google index of internet job-search activity and find 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 debit or credit cards is in principle observable. 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 verify the monthly aggregate provided by the CPA against the corresponding sum of daily aggregates provided by Interac; these match exactly. The daily or even higher frequency data may be valuable in the study of economic effects of transitory extreme events, as we have noted above; for our present purpose, however, the monthly aggregate is the finest that we use.

The payments system variables available to us, aggregated to the monthly frequency from January 2000 through December 2009 (credit cards) or April 2012 (cheques and debit cards), are the following:

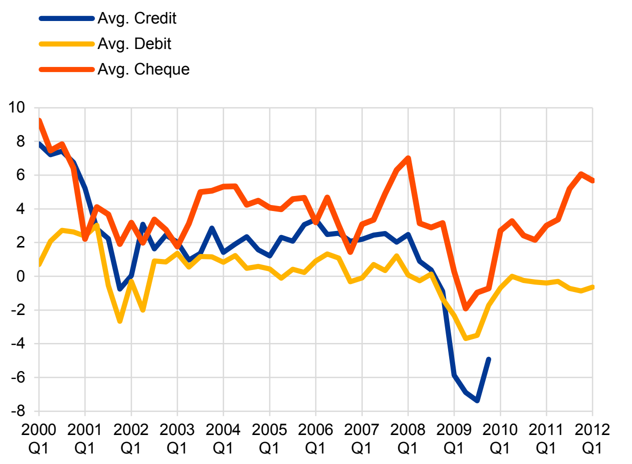
- Debit: We measure point of sale (POS) payments that clear between two institutions. This involves a debit from the consumer's bank account and a credit to the merchant's account. This captures more than 80% of the approximately 4.5 billion (in 2013) annual debit transactions in the economy. We aggregate all debit transactions for the members of the Canadian Payments Association (CPA). We have data on both the aggregate value and volume of all debit transactions.

- Credit: Visa and MasterCard dominate the Canadian credit card market, accounting for about 90 percent of all credit card transactions in the economy. These cards are issued by Canadian banks. We aggregate the monthly value of all combined Visa and MasterCard transactions. These data were obtained from the Canadian Bankers Association (CBA).

- Cheques: As with debit cards, we capture all small cheques that clear between 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.

Figure 1 plots the year-over-year growth rates of average transaction values of all three types from 2000 to 2009 (for credit cards), and 2000 to 2012 (for cheques and debit cards). These three series are evidently informative about economic activity, especially during downturns. The sample contains 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. In that period, which includes the attacks of 9/11, we observe that both average debit and credit transactions showed negative growth rates.

Figure 1
Annual growth rates of average transaction values: cheques, credit and debit, monthly



A caveat concerning these data is that payments may rise or fall for reasons other than an overall increase or decrease in spending; they also change as consumers choose to switch between payments technologies. For example, a consumer choosing to switch to a credit card from a debit card for grocery purchases would result in a growth in credit card transactions and a fall in debit transactions. For this reason, using any series in isolation could lead to false signals about economic activity, whereas using all of them in a model would endogenise a consumer's choice of payment technology. However, unless short-term fluctuations in relative use of payments methods is substantial, a single series may remain an adequate indicator of short-run changes in consumer expenditure.

A notable payments technology 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 transfers among individuals) and so it is difficult to track accurately the cash component of any monetary aggregate that is being spent in a given period. However, our base model does incorporate the growth of narrow money, which is one component of the Composite Leading Index, which we discuss further below. Second, cash is most often used for small transactions, and so cash purchases may be less highly correlated with aggregate spending fluctuations, which are most influenced by consumer spending decisions on larger discretionary items. Arango, Huynh and Sabetti (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 most widely used for transactions under $15, with 59% of the value of all such transactions being made using cash. By contrast cheques are almost never used for retail purchases in Canada, although as mentioned above they capture large, infrequent payments that could crowd out discretionary purchases made using debit and credit, and so are worth retaining for this purpose.

2.2 Base-case indicators

Although a visual inspection of Figure 1 certainly suggests that payments variables are correlated with the business cycle, we need to assess the information content of these variables relative to indicators that are already regularly compiled and monitored. In other words, we need to assess whether they provide any new information at the margin.

Apart from lagged GDP growth, we also consider two additional variables, although one of them incorporates the movements of ten different indicators:

1. Composite Leading Index (CLI): The CLI is constructed as a simple average of ten different variables that capture movements in the business cycle from various sectors, standardised such that its mean and standard deviation correspond to that of GDP growth. The ten variables that comprise the CLI are:

   - Group 1: Leading indicators
     housing index (housing starts and MLS housing sales); business and personal services employment; Toronto stock exchange index; narrow money supply (real); U.S. CLI;

   - Group 2: Manufacturing
     average work week (hours); new orders, durables; shipments/inventories of finished goods;

   - Group 3: Retail trade
     furniture and appliance sales; other durable goods sales.

The CLI for a given month *t* is generally released in the third week of month *t* + 1. The key benefits of the CLI are that it captures movements in a broad range of sectors in a single number, and that it is released in a relatively timely manner. However, within the CLI some of the components are measured with a lag, as they rely on survey data. This is the case for the retail trade variables, 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, data for these components actually reflect observations for month *t* — 2. In addition, the U.S. CLI applies to month *t*— 1.

2. Unemployment rate: Although the CLI captures the health of the labour market through its inclusion of private sector employment numbers, we have found that the overall unemployment rate itself, which would incorporate the impact of public sector hiring, sometimes has 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.

When using these variables in our nowcasting equations we convert them into quarterly growth rates in order to match the relevant GDP growth rate being studied, as well as to induce approximate stationarity.

Inspection of the year-over-growth rates of the CLI and of the unemployment rate (not shown) suggests that these variables have movements corresponding with the business cycle of the last ten years, with the CLI having a tendency to move prior to the unemployment rate, suggesting that the unemployment rate may in fact be a lagging indicator of economic activity rather than a coincident indicator.

The remainder of this study is concerned with whether payments variables contain any relevant information that is not already captured by the CLI, the unemployment rate and the dynamics of GDP growth itself. To make this assessment we need to ensure that the models incorporate only information available at the time 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.

2.3 Timing of data releases

From the discussion above, we can write

$$y = f(y_{-i}, CLI, u, PAY) \qquad (1)$$

where y and y_{-i} are real GDP growth and its lags, cli is the growth rate of the Composite Leading Index, u is the change in the unemployment rate and PAY is a vector of growth rates of payments variables, which may include the value and volume of debit, credit and chequing transactions.

The growth rates are computed as quarter-over-quarter; results for year-over-year GDP growth are not materially different. Our base-case model omits the payments variables; we consider four alternative models which respectively contain (i) the growth rates of the value and volume of debit card transactions; (ii) the growth rates of the value and volume of credit card transactions; (iii) the growth rates of the value and volume of cheque transactions; (iv) the growth rates of the values and volumes of debit cards, credit cards and cheques.

We have omitted time subscripts from (1), as these would vary according to the precise time at which an analyst would be required to generate a nowcast. However, for estimation and nowcasting purposes we need to specify the appropriate datings. In what follows we assume that one is required to generate a nowcast of GDP growth for quarter t, with the first nowcast generated on the first day of the quarter, and a new nowcast generated on the first day of each subsequent month until the growth rate is released, which would be at the end of the second month of quarter *t* + 1. For example, the third quarter of a year occurs in the months of July, August and September, and the actual growth rate for Q3 would be released around 30 November. Thus, an analyst would produce a nowcast for Q3 on 1 July, 1 August, 1 September, 1 October and 1 November, for a total of five nowcasts. Presumably the nowcast will become more precise the closer its production to the actual release date, as new data become available. With five different nowcast production dates, and with new monthly data becoming available for each one, the time subscripts on the explanatory variables in (1) will vary correspondingly within the quarter.

The release dates for GDP, the CLI and the unemployment rate are regular and known in advance. GDP (either quarterly or the monthly update) is always released two months after a given month; the CLI around the third week after a given month; and the unemployment rate around the second week after a month. By contrast, since payments data are recorded electronically, they are in principle available at a daily frequency, and can be released the next business day.

Given the release dates above, we can specify the five variants of (1) that an analyst can estimate for each of the five different nowcasting points for a given quarter t. These time subscript specifications are provided in Table 1, and to facilitate the discussion we provide an illustration using *t* =Q3. In each case a subscript *t* indicates a full-quarter value, while a subscript ⅓ (*t*), for example, denotes a monthly value for the first month (i.e. the first third) of the quarter *t*.

Table 1

Data release dates and nowcasting equation specification

Quarter t	Available Data	Example: t=Q3	Available Data
1st Month	Quarterly: $y_{t-2}, CLI_{t-2}, u_{t-2}, PAY_{t-1}$	1 July	Quarterly: GDP (Q1), CLI (Q1), *u* (Q1), PAY (Q2)
	Monthly: $y_{\frac{1}{3}(t-1)}, CLI_{\frac{2}{3}(t-1)}, u_{\frac{2}{3}(t-1)}$		Monthly: GDP (April), CLI (May), *u* (May)
2nd Month	Quarterly: $y_{t-2}, CLI_{t-1}, u_{t-1}, PAY_{t-1}$	1 August	Quarterly: GDP (Q1), CLI (Q2), *u* (Q2), PAY (Q2)
	Monthly: $y_{\frac{2}{3}(t-1)}, PAY_{\frac{1}{3}(t)}$		Monthly: GDP (May), Pay (July)
3rd Month	Quarterly: $y_{t-1}, CLI_{t-1}, u_{t-1}, PAY_{t-1}$	1 September	Quarterly: GDP (Q2), CLI (Q2), *u* (Q2), PAY (Q2)
	Monthly: $CLI_{\frac{1}{3}(t)}, u_{\frac{1}{3}(t)}, PAY_{\frac{2}{3}(t)}$		Monthly: CLI (July), *u* (July), PAY (August)
4th Month	Quarterly: $y_{t-1}, CLI_{t-1}, u_{t-1}, PAY_{t}$	1 October	Quarterly: GDP (Q2), CLI (Q2), *u* (Q2), PAY (Q3)
	Monthly: $y_{\frac{1}{3}(t)}, CLI_{\frac{2}{3}(t)}, u_{\frac{2}{3}(t)}$		Monthly: GDP (July), CLI (August), *u* (August)
5th Month	Quarterly: $y_{t-1}, CLI_{t}, u_{t}, PAY_{t}$	1 November	Quarterly: GDP (Q2), CLI (Q3), *u*(Q3), PAY (Q3)
	Monthly: $y_{\frac{2}{3}(t)}, PAY_{\frac{1}{3}(t+1)}$		Monthly: GDP (August), PAY (October)

In addition to whatever quarterly values are available, monthly data are incorporated into the nowcast by using the available monthly data to compute average observations for the incomplete quarter. For example, when a nowcast is generated on 1 July, an analyst would have CLI and unemployment data for May. The quarterly growth rate of these variables for April and May (i.e. relative to January and February) is used as a proxy growth rate for these variables for Q2. The more data available for a quarter, the better on average our estimate of the final value for that quarter should be, and therefore the more accurate our nowcast.

3 Nowcasting Canadian GDP Growth

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

As well, there are different measurements of real GDP growth in which an analyst might take an interest, distinguished primarily along the dimensions of vintage and time span. We 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 respect to the accuracy of their forecasts, and good forecasts of first-release numbers enhance the credibility of policymakers. From the point of view of choice of the most appropriate policy at a given time, however, forecast accuracy relative to the best (presumably latest-vintage) estimate of GDP is the relevant criterion. Throughout the forecasting period we account for changing vintages of GDP data used as predictors, ensuring that we use only the vintage that was available to forecasters at the time that nowcast would have been produced. We also repeatedly seasonally adjust our payments data using X-11 to ensure that no forward-looking information is introduced into the nowcasting evaluation.

We compute results on two spans of data. The first, through the end of 2009, contains the largest selection of variables. Credit card data are not available to us on the same basis from 2010 on. Therefore the longer data set which extends through April 2012 contains debit and cheque data, but not credit card data.[6]

Our main sample begins in 2000Q1 and ends in 2009Q4, for a total of 40 quarterly observations. This small sample size, limited by the frequency of the GDP data, implies that results can only be suggestive, not conclusive. In our nowcasting exercise we use the first 20 observations for initial estimation of our parameters, which are used to produce a nowcast for 2005Q1. The sample is updated by one quarter, parameters are re-estimated and a nowcast produced for 2005Q2. This process is repeated until we obtain nowcasts for 2009Q4. The extended sample, omitting credit card data, allows us to extend the nowcast sequence through 2012Q1.

---

[6] Vintage data on real GDP in chained 2007 dollars are available via archived versions of Statistics Canada catalogue 15-001X, produced through December 2012 (October 2012 monthly GDP estimate). Thereafter vintage data reported on a comparable basis are not currently available. 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, in the traditional notation) quarterly, a seasonally adjusted GDP estimate is made available at the monthly frequency.

Given the different time subscripts associated with the variables in Table 1, we treat each of the five specifications as a different model and we track the nowcasting performance of each specification over the full nowcasting sample. For example, for the specification in which a nowcast is produced during the first month of each quarter, we track the accuracy of nowcasts produced on 1 January, 1 April, 1 July and 1 October, i.e. the first month of each quarter. The next specification uses the data available at the beginning of the second month, and so a new set of nowcasts is produced on 1 February, 1 May, 1 August and 1 November. We repeat this for each of the five periods for which a nowcast for quarter *t* is required, as discussed in Section 3.

In Figure 2a we plot the nowcasts of quarterly GDP growth using the base-case model (i.e. without the payments variables), using the data available at the beginning of each month. We can observe that the nowcasts produced at the beginning of the quarter (i.e. the first month) are the least accurate. Notably, they miss many of the turning points in GDP growth, and miss the timing of the recession that began in 2008Q4. However, as more data become available during the quarter, we see that the nowcasts approach actual GDP growth. By the fifth month a nowcast for GDP growth is produced with knowledge of the growth rates for the first two months of the quarter, so it is of course easier to nowcast the full quarter.

Interestingly, it appears that by around the third nowcast of the quarter, analysts should be able to capture fairly accurately the turning points in GDP growth. For example, the trough in GDP growth was accurately captured as 2009Q1, so by June 2009 (the third month of 2009Q2), analysts should have been predicting an improvement in economic activity using the base-case model.

Figure 2b plots a new set of nowcasts, generated by the model augmented with debit card transactions (both values and volumes). As with Figure 2a we clearly see improvements in nowcasting accuracy that accrue over time, with those generated in the first month being the least accurate, and those generated in the fifth month being the most accurate. In comparing the two figures visually we may detect modest nowcast improvements as we track the Month 2 nowcasts during the 2008-09 recession. The debit-augmented Month 2 nowcast (Figure 2b) turns downwards sooner then does the base case, and appears to be slightly more accurate with respect to depth of the recession. However, to judge whether the payments variables contribute to lowering nowcast errors in a substantial manner we will study the root mean squared (nowcast) errors (RMSE’s), which are presented in tables 2 and 3 (extended sample) and figures 3 and 4.

Figure 2a
Historical nowcasts of quarterly %Δ real GDP by month of production

Base case, 2005Q1-2012Q1

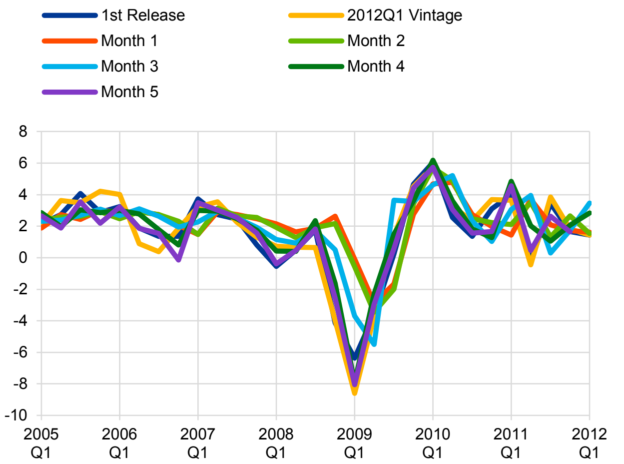


Figure 2b
Historical nowcasts of %Δ real GDP by month of production

Debit payments added, 2005Q1-2012Q1

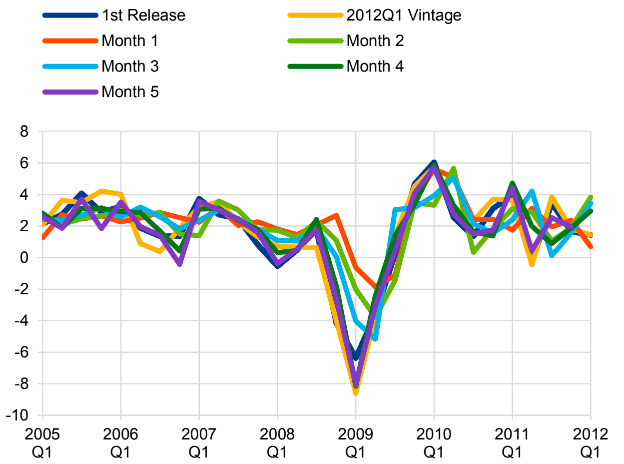


Figure 3
RMSE (%) of nowcast by month of production and model

Base case, 2005Q1-2009Q4

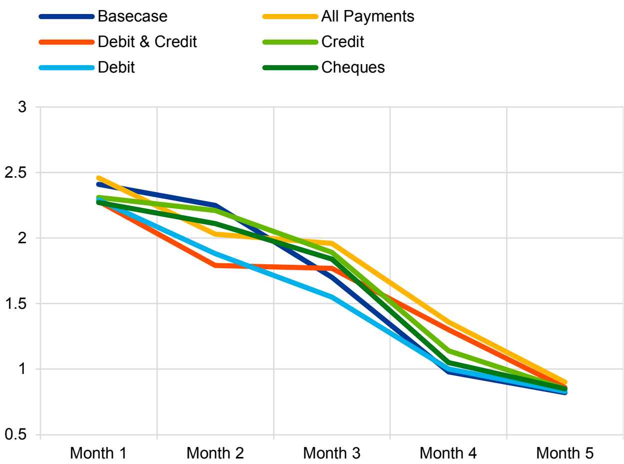


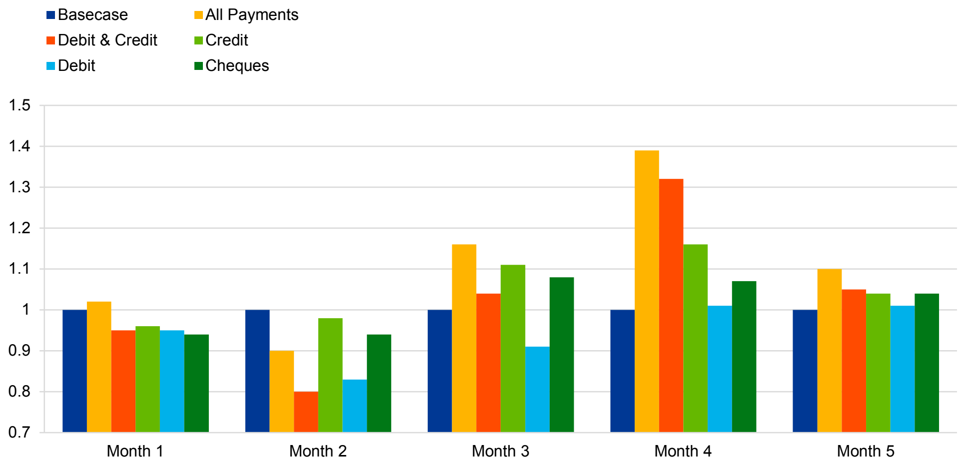
Figure 3 shows these RMSE's of the base-case model generated for each of the five months, the RMSE's of the aggregated-payments model, and the RMSE's of the models that augment the base case with each of the three payments variables separately. This figure and Figure 4 following use the data through 2009Q4, the time period for which all payments variables are available to us. Clearly the RMSE's fall the farther we are into a quarter, and are lowest when produced in the fifth month. The magnitude of RMSE reduction over the five-month nowcast range is quite substantial; the RMSE values for percentage real GDP growth begin at more than 2 percentage points when generated in the first month, falling to less than 0.9 percentage point when generated in the final month before the data is released.

With respect to the payments variables, we observe indications of modest improvements in nowcast accuracy during the first two months of the nowcast period. The numerical results in tables 2 and 3 tend to show a general tendency towards small loss reductions in these first two months, ranging up to a maximum of 20% in the first sample, and only up to 8% in the more limited data of the longer sample period. After the first two months, with the first release of the previous quarter's GDP growth being available, there is no further measured value added from the payments variables, and in these small sample sizes the loss of degrees of freedom can lead to substantially higher forecast loss. That is, the suggestion from these results is that the value of payments variables arises from their immediacy and may improve the accuracy of the very first nowcasts; once other measures become available, however, the marginal contribution disappears. The sample size of 20 nowcast periods is too small to make any claim about the statistical significance of the reduction[7]. We note however that the out-of-sample period is noteworthy in that it incorporates the 'great recession' of 2008-09. In particular, 2009Q1 was the largest proportionate quarterly drop in real GDP ever recorded, and the usefulness of payments data in reducing the recognition lag in recessions is of some interest.

To give a visual impression of the magnitude of the RMSE changes, Figure 4 plots the RMSE's of the alternative models relative to the base case.

Figure 4
Relative RMSE of nowcast by month of production and model

Base case, 2005Q1-2009Q4



[7] In principle, testing the significance of a reduction in RMSE for nested models can be performed using a procedure such as that proposed by Clark and McCracken (2001).

4 Conclusion

Nowcasts matter for many decision-makers, and the present results emphasise that the accuracy of nowcasts varies considerably with the amount of information available to an analyst, as the average nowcast error can be 65% lower if produced just prior to a data release compared with one produced at the beginning of a quarter.

We also assess how electronic payments data, which are in principle available very quickly, can contribute to producing nowcasts. We find some suggestive evidence of an improvement in accuracy of the earliest nowcasts, primarily through the inclusion of debit card payments in the predictive model. We do not find evidence that endogenising a substitution between payment types helps substantially to reduce false signals about economic activity from any single payment type. The apparent improvement in nowcast accuracy through the inclusion of debit card information is observed for the first two months of the nowcast period, but once the previous quarter's GDP value is observed (month 3), a marginal contribution of these payments variables is no longer detectable. Again, however, we caution that, because of the small numbers of quarterly GDP measurements available (the projection of 'small data' onto 'big data'), these results are suggestive, but cannot be statistically conclusive.

A desirable further development of this research would be to combine electronic transactions with other data that can be measured with some accuracy at a daily frequency, and a framework can be established that would automate the generation of nowcasts on a daily basis as new data is observed. In this context we can also find more effective methods for combining data at different frequencies within a single model. The state space approach used by Armah (2011) would be one avenue by which to pursue this, as would a MIDAS mixed-frequency regression approach (e.g. Andreou, Ghysels and Kourtellos (2010)).

References

Andreou, E., E. Ghysels and A. Kourtellos (2010), “Regression Models with Mixed Sampling Frequencies”, Journal of Econometrics 158, 246-261.

Arango, C., K. Huynh and L. Sabetti (2011), “How Do You Pay? The Role of Incentives at the Point-of-Sale”, Working Paper 2011-23, Bank of Canada.

Arango, C., K. Huynh, B. Fung and G. Stuber (2012), “The Changing Landscape for Retail Payments in Canada and the Implications for the Demand for Cash”, Bank of Canada Review, Bank of Canada, Ottawa.

Armah, N. (2011), “Predictive Densities and State Space Nowcasting”, Working Paper, Bank of Canada.

Aruoba, S. B., F. X. Diebold and C. Scotti (2009), “Real-Time Measurement of Business Conditions”, Journal of Business and Economic Statistics 27, 417-427.

Bańbura, M., D. Giannone and L. Reichlin (2010), “Nowcasting”, Working paper 1275, European Central Bank, Frankfurt.

Burstein, A., M. Eichenbaum, and S. Rebelo (2005), “Large Devaluations and the Real Exchange Rate”, Journal of Political Economy 113, 742-784.

Camacho, M. and G. Perez-Quiros (2008), “Introducing the Euro-STING: Short-Term Indicator of Euro-Area Growth”, Working Paper, Bank of Spain.

Campbell, J.R. and B. Eden (2014), “Rigid Prices: Evidence from U.S. Scanner Data”, International Economic Review 55, 423-442.

Choi, H. and H. Varian (2012), “Predicting the Present with Google Trends”, Economic Record 88, 2-9.

Clark, T.E. and M.W. McCracken (2001), “Tests of Equal Forecast Accuracy and Encompassing for Nested Models”, Journal of Econometrics 105, 85-110.

D’Amuri, F. and J. Marcucci (2012), “The Predictive Power of Google Searches in Forecasting Unemployment”, Working paper, Banca d’Italia.

Espinoza, R., F. Fornari and F.J. Lombardi (2012), “The Role of Financial Variables in Predicting Economic Activity”, Journal of Forecasting 31, 15-46.

Federal Reserve System (2014), “The 2013 Federal Reserve Payments Study” and “Summary Report and Initial Data Release”, Revision of July 2014. Federal Reserve System, Washington, DC.

Galbraith, J. W. (2003), “Content Horizons for Univariate Time Series Forecasts”. International Journal being of Forecasting 19, 43-55.

Galbraith, J. W. and G. Tkacz (2013), “Analyzing Economic Effects of September 11 and Other Extreme Events Using Debit and Payments System Data”, Canadian Public Policy 39, 119-134.

Galbraith, J. W. and G. Tkacz (2007), “Forecast Content and Content Horizons for some Important Macroeconomic Time Series”, Canadian Journal of Economics 40, 935-953.

Giannone, D., L. Reichlin and D. Small (2008), “Nowcasting: The RealTime Informational Content of Macroeconomic Data”, Journal of Monetary Economics 55, 665-676.

Gicheva, D., J. Hastings and S. Villas-Boas (2010), “Investigating Income Effects in Scanner Data: Do Gasoline Prices Affect Grocery Purchases?” American Economic Review: Papers & Proceedings 100, 480-484.

Mitchell, W. C. and A. F. Burns (1938), “Statistical Indicators of Cyclical Revivals”, In Moore, G. H. (Ed.) Business Cycle Indicators, Vol. 1. Princeton: Princeton University Press, 184-260, Reprinted 1961.

Nunes, L. C. (2005), “Nowcasting Quarterly GDP Growth in a Monthly Coincident Indicator Model”, Journal of Forecasting 24, 575-592.

Shankar, V. and R. N. Bolton (2001), “An Empirical Analysis of Determinants of Retailer Pricing Strategy”, Marketing Science 23, 28-49.

Silver, M. and S. Heravi (2001), “Scanner Data and the Measurement of Inflation”, The Economic Journal 111, F383-F404.

Stock, J. and M. W. Watson (1989), “New Indexes of Coincident and Leading Economic Indicators”, NBER Macroeconomics Annual 1989, 351-394.

Stock, J. and M. W. Watson (1991), “A Probability Model of the Coincident Economic Indicators”, In Leading Economic Indicators: New Approaches and Forecasting Records, Lahiri, K. and Moore, G.H. (eds) Cambridge: Cambridge University Press, 63-85.

Tkacz, G. (2010), “An Uncertain Past: Data Revisions and Monetary Policy in Canada”, Bank of Canada Review, Spring, 41-51.

Annex

Table 2

Root mean squared forecast errors, *k* =1, first-release % real GDP growth

Out-of-sample nowcast period 2005Q1 - 2009Q4

Panel A: RMSE

Model	Month 1	Month 2	Month 3	Month 4	Month 5
Base case	2.41	2.25	1.70	0.98	0.82
All payments	2.46	2.03	1.96	1.36	0.90
Debit & credit	2.28	1.79	1.77	1.30	0.86
Credit	2.31	2.21	1.89	1.14	0.85
Debit	2.29	1.88	1.55	1.00	0.83
Cheques	2.27	2.11	1.84	1.05	0.85

Panel B: RMSE vs base case

Model	Month 1	Month 2	Month 3	Month 4	Month 5
Base case	1.00	1.00	1.00	1.00	1.00
All payments	1.02	0.90	1.16	1.39	1.10
Debit & credit	0.95	0.80	1.04	1.32	1.05
Credit	0.96	0.98	1.11	1.16	1.04
Debit	0.95	0.83	0.91	1.01	1.01
Cheques	0.94	0.94	1.08	1.07	1.04

Table 3

Extended sample results

Root mean squared forecast errors, *k* =1, first-release % real GDP growth

Out-of-sample nowcast period 2005Q1 - 2012Q1

Panel A: RMSE

Model	Month 1	Month 2	Month 3	Month 4	Month 5
Base case	2.27	2.13	1.90	1.14	0.86
Debit & cheque	2.27	1.99	1.94	1.05	0.93
Debit	2.14	1.97	1.85	1.14	0.88
Cheques	2.27	1.99	1.98	1.03	0.92

Panel B: RMSE vs base case

Model	Month 1	Month 2	Month 3	Month 4	Month 5
Base case	1.00	1.00	1.00	1.00	1.00
Debit & cheque	1.00	0.93	1.02	0.92	1.08
Debit	0.94	0.92	0.97	1.00	1.02
Cheques	1.00	0.93	1.04	0.90	1.07

Acknowledgements
The paper was presented at the ECB's workshop on using big data for forecasting and statistics, which was held in Frankfurt am Main on 7 and 8 April 2014. We would like to thank Marco Lombardi and participants in this workshop, the Bank of Canada's workshop on nowcasting and short-term forecasting, the International Symposium on Forecasting, and seminar participants at Dalhousie, Mount Allison and Queen's universities for valuable comments on earlier drafts of this paper. CIRANO (*Centre Interuniversitaire de recherche en analyse des organisations*), the Social Sciences and Humanities Research Council of Canada (SSHRC) *and Fonds quebecois de la recherche sur la société et la culture* (FQRSC) either provided facilities or the financial support for this research. We are also grateful to Acxsys Corporation, the Canadian Payments Association, and the Canadian Bankers' Association for providing us with the electronic payments data. Gavril Petrov provided outstanding research assistance. Both authors are also affiliated with CIRANO, and Galbraith with CIREQ.

John W. Galbraith
Department of Economics, McGill University; e-mail: john.galbraith@mcgill.ca

Greg Tkacz
Department of Economics, St. Francis Xavier University; e-mail: gtkacz@stfx.ca

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Internet	www.ecb.europa.eu

ISSN	2314-9248 (online)
ISBN	978-92-899-1906-7
DOI	10.2866/444926
EU catalogue number	QB-BF-15-002-EN-N