Electronic Transactions as High-Frequency Indicators of Economic Activity

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Abstract

Since the advent of standard national accounts data over 60 years ago, economists have relied on monthly or quarterly data supplied by central statistical agencies for macroeconomic modelling and forecasting. However, technological advances of the past several years have resulted in new high-frequency data sources that could potentially provide more accurate and timely information on the current level of economic activity. In this paper we explore the usefulness of electronic transactions as real-time indicators of economic activity, using Canadian debit card data as an example. These data have the advantages of daily availability and the high market penetration of debit cards. We find that (i) household transactions vary greatly according to the day of the week, peaking every Friday and falling every Sunday; (ii) debit card data can help lower consensus forecast errors for GDP growth; (iii) debit card transactions are correlated with Statistics Canada's revisions to GDP; (iv) high-frequency analyses of transactions around extreme events are possible, and in particular we are able to analyze expenditure patterns around the September 11 terrorist attacks and the August 2003 electrical blackout.

Key words: data revisions, electronic transactions, real-time data, nowcasting
JEL Classification numbers: E17, E27, E66

We thank the Interac Organization, and in particular Eric Chue and Geoff Robinson, for supplying us with the data on debit card transactions, and Bryan Campbell and Steve Murphy who provided vintage macroeconomic data through CIRANO (*Centre Interuniversitaire de recherche en analyse des organisations).* Workshop participants at the Bank of Canada, the CIRANO workshop on Data Revision in Macroeconomic Forecasting, Statistics Canada, Carleton and McGill universities offered valuable comments and suggestions, and we thank especially Jason Allen, Jean-Marie Dufour, Bob Fay, Sharon Kozicki, and Varya Taylor. Stephen Doxey and Timothy Grieder provided fine research assistance. The views expressed by Tkacz in this paper are exclusively his own and should not be attributed to the Bank of Canada.

1. Introduction

Policy makers regularly require accurate and timely information on the current state of the economy in order to make informed decisions. Official estimates of Gross Domestic Product (GDP), however, require some time to compile, and by the time the official number is released, many decisions dependent upon the value will already have been made. Nunes (2005) notes that among developed countries, the delay required to release a new quarterly GDP figure ranges from one month for the United States, to up to four months in many European countries.

Apart from the timeliness of new data releases, decision makers must also be aware that initial estimates of economic activity are often subject to substantial future revisions as more information is gathered on the state of the economy. Stekler (1967) was the first to highlight this issue for economic forecasters. In a different context, Orphanides (2001) shows that real-time estimates of the output gap (i.e. deviations between actual and potential output) can sometimes differ by more than two percentage points when revised data are used instead of first-release data. Clearly, monetary policy makers basing their interest rate-setting decisions on first-release numbers could potentially make ill informed decisions. Examples of the magnitudes of revisions to other macroeconomic variables are discussed in Croushore and Stark (2001).

It is therefore often useful for decision makers to augment the early releases of information supplied by central statistical agencies with additional, often higher-frequency, data. At the National Bureau of Economic Research (NBER), there exists a long history of documenting leading and coincident indicators of economic activity (e.g. Burns and Mitchell, 1946). More recently, Stock and Watson (1989, 1991) extract the common component of a number of quarterly, monthly, and some weekly, data series in order to construct a single monthly index of economic activity. Of course, some of the components of such indices (such as employment data) are also subject to revision.

Technological advances of the last several years have resulted in a cornucopia of additional data that have as yet not been fully exploited by economic analysts. Check-out scanners in stores have emerged in the last twenty years, for example, and are probably the best known source of "new" economic data. For decision makers at the firm level, scanner data can provide stores with real-time information on their inventory status. A limitation of check-out data for macroeconomists, however, is that it is largely proprietary, and so nationwide aggregations are seldom found, although limited aggregation of such data is often performed by external firms for the analysis of a specific product or industry. For this reason, scanner data in economics are most often used in the context of empirical industrial organization studies. For example, Shankar and Bolton (2004) use scanner data to study the determinants of retail prices for products such as spaghetti sauce and frozen waffles.

In macroeconomics, scanner data use has largely been limited to the assessment of overall price movements. For example, Burstein, Eichenbaum and Rebelo (2005) use supermarket scanner data as one indicator of inflation in Argentina for 2001-2002, while Hausman and Leitbag (2004) and Silver and Heravi (2001, 2005) consider scanner data to develop more accurate measures of inflation. We know of no study that has considered scanner data as an indicator of current economic activity, likely because of the aggregation problem mentioned above.

For the purpose of forecasting (or "nowcasting," i.e. estimating a current state) economic activity, it would be desirable for a new data source to possess the following properties: the data should be

- broadly defined, thereby capturing economic activity for several products, industries, demographics and geographic locations;
- compiled by a single source, for timeliness;
- measured accurately, with known transaction date (and, ideally, time of day).

One potential data source that could satisfy these three properties is electronic debit card purchases. Debit cards are a relatively new means of payment which has gained in popularity in the past 15 years, whereby a consumer can pay for a purchase at a merchant by having funds directly withdrawn from his or her bank account. There are a number of benefits that we can identify with this particular data source: a purchase made using a debit card results in an immediate rise in personal consumption expenditures, which is the largest component of GDP; debit card transactions are recorded instantaneously and electronically, thereby minimizing errors; at least in the case of Canada, a single entity (the Interac Organization) aggregates all transactions, so that reliable consumption statistics are available on a daily (and in principle higher) frequency. Note that we wish to distinguish actual purchases made with debit cards from cash withdrawals; the latter may be treated differently, since the funds withdrawn can be used for consumption at a later date.

In the present study we are interested in assessing the usefulness of such electronically recorded transactions data for macroeconomic analysis, using daily Canadian debit card data as an example. To do so we consider several potential uses of these data. First, we examine the extent to which such transactions are correlated with forecast errors at low (quarterly) frequencies (and therefore whether transactions can be used to predict first-release measurements); we assess several forecasts. For this purpose, we will measure economic activity using total GDP, as well as aggregate consumption and non-durable consumption. Second, recognizing that National Accounts data are often revised, we will consider whether debit cards can help predict the revisions to GDP and consumption, thereby potentially providing decision- makers with more reliable estimates of economic activity in real time. Finally, we measure the short-term impact of two well-known shocks in a high-frequency setting, which would be impossible using quarterly official data: in particular, we examine the September 11 terrorist attacks and the August 2003 electrical blackout.

This paper is structured as follows. In the next section we discuss our debit card data source, the forecast and measurement errors of national accounts data are examined in Section 3, while Section 4 analyzes the two shocks. The final section offers some concluding remarks.

2. Transactions data

2.1 Debit cards: background

One reason that Canadian debit card data potentially provide a useful example of the value of electronic transactions data lies in the fact that Canadians are among the most intensive users of this means of payments, already averaging nearly 82 transactions per person, or about one every four days, by 2003. Pilot projects for debit card terminals were launched in Canada in 1991, and adoption of this new means of payments has grown steadily ever since.[1] With 86 per cent of Canadians owning a debit card, it has become the preferred means of payments for many individuals since 2000. In 2004, 47 per cent of transactions were conducted with debit cards, compared to 29 per cent with cash, 20 per cent with credit cards and fewer than 4 per cent with cheques.

By contrast, in the United States the general adoption of this new technology has been slower. Gerdes et al. (2005) note that the number transactions using electronic means of payments (which includes both credit and debit card transactions) only exceeded the number of cheque payments for the first time in 2003. Furthermore, for that year in the United States the number of debit card transactions (15.6 billion) lagged credit card transactions (19 billion), although this is no longer the case (Borzekowski et al. 2008). Humphrey, Pulley and Vesala (2000) outline some reasons for the fact that adoption of electronic payments technology has been somewhat slower in the United States than elsewhere. Borzekowski et al. 2008 study consumer use of debit cards in the U.S. in detail, relating their use to demographic factors and pricing of card transactions, and in particular are able to estimate the response of debit card use to transaction fees.

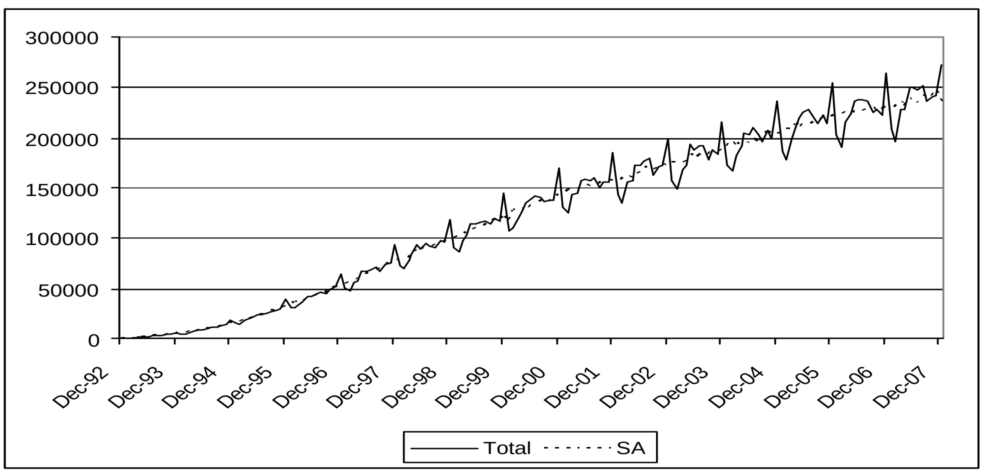
In Canada, where over 2.8 billion debit card transactions were made in 2004, the nominal dollar value of debit card purchases amounted to $124 billion that year. With GDP of $1.29 trillion, debit card purchases represented 10 per cent of the economy's expenditures. Since debit card expenditures are almost exclusively assigned to households, we further note that these purchases represented 17 per cent of total household expenditures ($721 billion). In short, debit card purchases can allow us to measure accurately, and at a very high frequency, significant components of consumption and GDP. As well, changes in other components of GDP, with the possible exception of government expenditures, will tend to be positively correlated with changes in debit purchases.

[1]Debit card transactions per inhabitant in 2003 were 81.7 in Canada, 74.6 in Sweden, 71.2 in the Netherlands, 70.6 in France, 63.4 in the U.S., and 56.7 in the UK. (Source: Interac Organization)

2.2 Time-series properties of debit card transactions

In Figure 1 we plot total monthly debit card transactions, as compiled by the Interac Organization.[2] Two features immediately emerge from this series: (i) transactions exhibit a strong seasonal pattern, with relative peaks occurring in the second and fourth quarters, and troughs in the first and third quarters; and (ii) monthly transactions have shown very rapid growth, far exceeding that of the overall economy, with transactions increasing from about 1.5 million in December 1992 to well over 200 million by the end of 2007. Since our measurements of the state of the economy are typically based on seasonally adjusted data, we adjust the debit card series using X11-ARIMA, the same procedure used to adjust the National Accounts data. The resulting seasonally adjusted debit card series is also shown in Figure 1, divided by the same constant.

FIGURE 1
Re-scaled number of monthly debit card transactions
Raw and seasonally adjusted, Dec 1992–Dec 2007

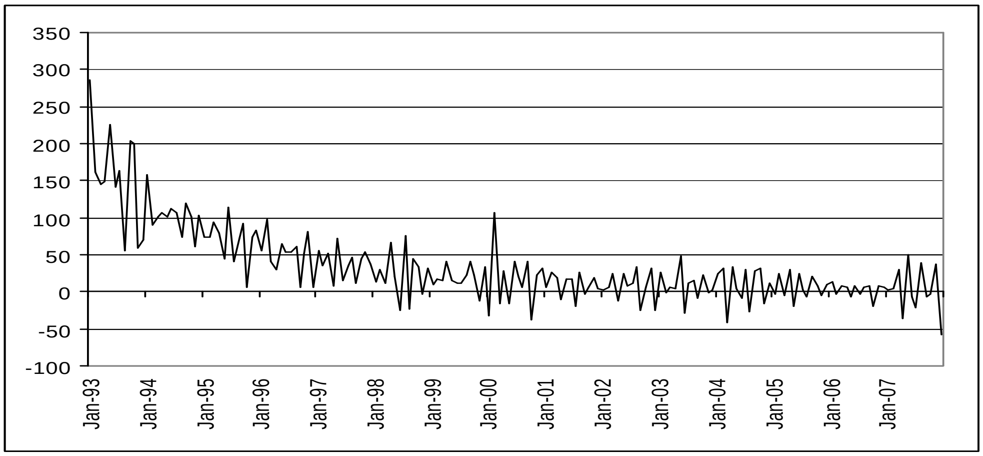


The second feature just noted is largely attributable to growth in the adoption of the new technology. The real economy grew by about 50% between 1992 and 2007, and debit card transactions grew by around 15,000%. This can be more clearly seen in Figure 2, where we plot the annualized growth rate of monthly debit card transactions. Growth rates are high early in the sample, but fall steadily as the proportion of firms that have installed debit card terminals increases. Around 1999 the downward trend in the growth rate begins to vanish, signalling that the technology has reached a mature

[2]In order to preserve the confidentiality of these numbers, the data are divided by a constant, which is not a simple power of 10. The numbers on the vertical axis are therefore not meaningful, but relative sizes are preserved.

state, with the result that growth rates observed from this point onwards largely reflect changes in economic activity.

Figure 2
Monthly growth rate of debit card transaction values
Seasonally adjusted, Jan 1993–Dec 2007

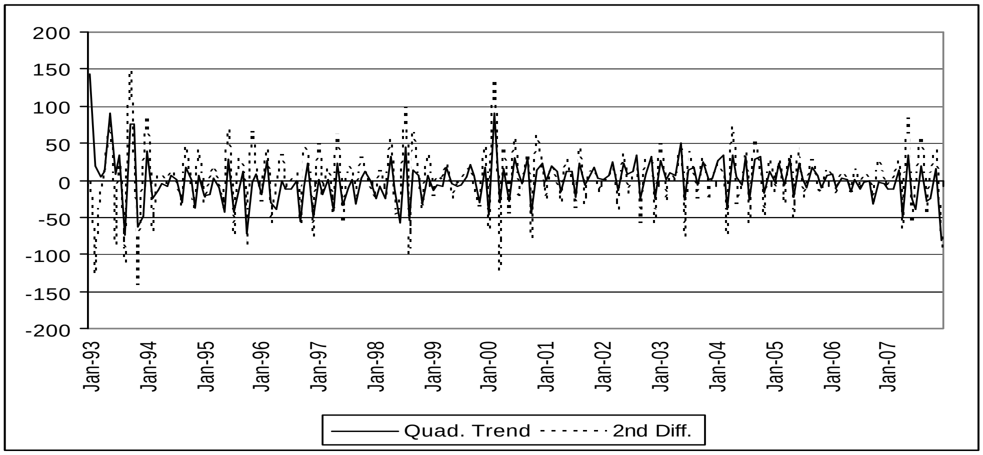


From a statistical perspective, and in the absence of suitable corrections, the downward trend in the growth rate of debit card transactions will obscure the signal of changes in economic activity. However, there are a number of ways in which we can correct for the growth rate in the adoption of debit card technology, each of which we will consider below:

- new technology adoptions are often modelled as following a quadratic growth rate; one can therefore regress debit card transactions on a quadratic time trend and use the subsequent residuals as our estimate of debit card transactions due to economic activity;
- changes in the growth rates of debit card transactions, instead of changes in the levels, can be analyzed;
- an estimated trend can be removed using a Hodrick-Prescott filter.

In Figure 3 we plot the series that emerge from the first two of these corrections; we do not use the Hodrick-Prescott filter as it is two-sided, and the resulting series will be used below in forecasting. They are similar in their general movements, although the second-differenced series exhibits more volatility. For the analysis that follows below we retain all three series in order to consider the robustness of the results to the method of modelling the technology adoption; stationarity is not rejected for any of the resulting growth rate series in standard tests.

FIGURE 3
Debit card transaction growth rates, adjusted for rate of technology adoption, Jan 1993–Dec 2007



2.3 Real-time national accounts data

In order to consider our ability to predict revisions to macroeconomic series using higher frequency data, we need a data base in which first release, second release, subsequent revisions, and final estimates of important macroeconomic quantities are stored. For the U.S., such data are maintained by the Federal Reserve Bank of St. Louis and are publicly available via internet. In Canada, no public institution has stored and provided these data. However, Campbell and Murphy (2007) describe such a data base which stores values of a number of macroeconomic quantities, including real GDP and several of its components such as aggregate and non-durable consumption expenditures. These quarterly data are available from the first quarter of 1971 through the latest published quarter (the present paper uses data through the fourth quarter of 2007, hereafter T) and are stored in the form of an upper triangular matrix, that is, entries are of the form $x_{t|\tau}$ where x is a variable of interest, t is the date to which a measurement applies, and τ is the date at which a measurement is recorded, with $\tau \geq t$. The main diagonal of the matrix therefore contains first-release estimates, $x_{t|t}$, while entries of the form $x_{t|\tau},\ \tau > t$, indicate the estimate of the value for date t that is current at some date τ which is after t. The sequence of values $x_{t|\tau},\ \tau = t, t+1, \ldots T$ typically contains the first release, at least two revisions, and occasional further changes resulting from base-year adjustments.

The availability of these different vintages of data allows us to investigate separately the usefulness of high-frequency transactions data in predicting first-release estimates and subsequent data revisions.

3. Can consensus forecast and measurement errors be predicted by electronic transactions?

3.1 Introduction

In assessing the potential contribution of electronic transaction data, we consider whether this variable could have improved the forecasts and measurements of some important macroeconomic quantities, namely quarterly GDP growth, consumption growth and non-durable consumption growth. The other GDP components are not considered, since household transactions do not enter into aggregate demand components arising from the business, government or foreign sectors. We do not consider finer disaggregations of consumption, such as expenditure on services, because these are not available in the Campbell and Murphy database that we use to investigate revisions.

There are two potential uses of the information contained within aggregate transactions, namely to improve the *forecasts* and *measurements* of the above variables. Forecasters use all the information available at time t to produce a forecast for the variable at $t+1$, whereas national accountants use all the available information at time t to produce an estimate of the variable at time t. If the information set is updated with an additional relevant variable, it might be possible to reduce both the forecast and measurement errors.

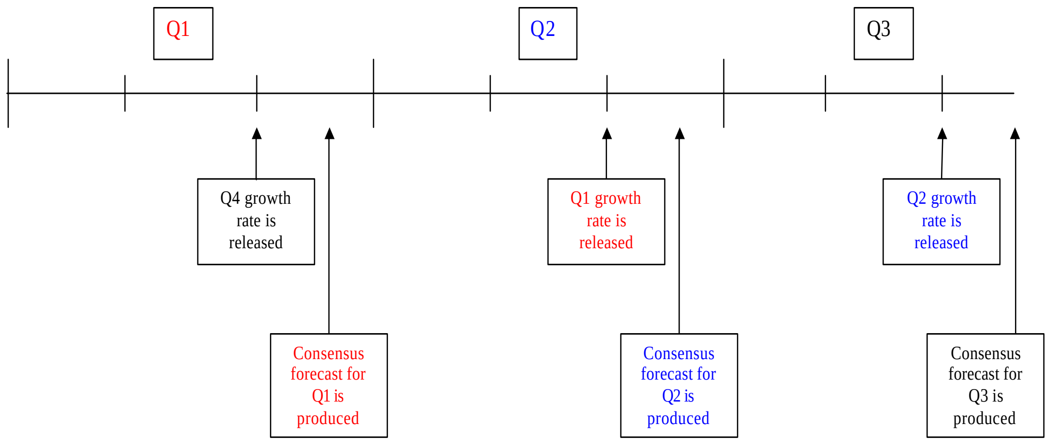
In what follows we study the forecast errors from a consensus forecast, produced by Consensus Economics Inc., which is the mean of fifteen forecasts produced by a sample of forecasters. Quarterly forecasts are produced for GDP and personal expenditure (and consumer price inflation, not treated here). The consensus forecast for a given quarter, as indicated in Figure 4 below, is produced approximately two weeks before the end of that quarter.

Similarly, we use the real-time data set of Campbell and Murphy (2007) , which is the most detailed source of real-time Canadian National Accounts data, to study the nature of the national accounts data revisions. In both cases, we attempt to model the observed errors using very simple equations that incorporate debit card transactions. If debit cards are statistically significant predictors of the errors, this will suggest that they have some utility in forecasting and/or measuring some key macroeconomic variables. If they are insignificant, then we would conclude that they are of little practical use, indicating that their information content is already captured within the information sets of forecasters and national accountants.

3.2 Errors

Let $N_{k,t}$ denote the officially-reported quarterly growth rate of any national accounts variable, where t is the quarter to which the growth rate pertains and k is the release number (or vintage) of the series. For example, if N represents GDP and t is 2005Q4, then $N_{1,2005Q4}$ denotes the first official estimate of the growth rate of GDP in 2005Q4. Given the delay required to compile and release national accounts data, the dates of such releases usually occur about two months after the actual quarter has ended; in this case, the first release of the GDP growth rate estimate for 2005Q4 occurred on 28 February, 2006. Figure 4 records the timeline for forecasts and data releases.

FIGURE 4
Timeline of forecasts and data releases



As more information is compiled, Statistics Canada will revise its estimate of the growth rate for (in this example) 2005Q4. The subsequent estimate is denoted as $N_{2,2005Q4}$, and is released the following quarter at the same time as the initial estimates for the growth rate of 2006Q1; specifically, the second estimate of 2005Q4 was released on 31 May, 2006. Future revisions of the 2005Q4 measurement can be represented similarly, with $k = 3, 4, 5, \ldots$ etc. We would expect that the magnitude of the revisions would decrease as k increases, as the statistical agency approaches more nearly the "true" growth rate for that quarter.

To carry out our assessment of the usefulness of transaction data we will consider consensus forecasting errors, which may be expressed as

$$E_{k,t} = (N_{k,t} - C_t) = (N_{1,t} - C_t) + (N_{k,t} - N_{1,t}), \tag{1}$$

where C_t represents the consensus forecast of a particular quantity of interest measured at time t. Since we are interested in the usefulness of debit card data both in improving upon the consensus forecast and in improving national accounts measurements and revisions, we will investigate not only whether incorporating debit card transactions is of value in reducing (typical values of) $E_{k,t}$ for different values of k, but also whether the revisions $(N_{k,t} - N_{1,t})$ can be predicted, and therefore whether information can be incorporated into the earliest measurement $N_{1,t}$ which would reduce the typical magnitude of revision. To this end, we investigate the transaction measure in simple equations that attempt to fit and predict the forecast errors and the measurement errors.

3.3 Descriptive statistics

We focus on the quarterly growth rates of three National Accounts variables: real GDP, total consumption and non-durable consumption. In Table 1 we present some basic descriptive statistics for the measurement and forecast errors, using the Campbell-Murphy (2007) vintage data. Some observations:

Measurement errors, $N_{k,t} - N_{1,t}$:

- GDP revisions tend to be fairly small on average over this sample period. The standard error of the revisions is around 0.5 in annualized quarterly data, and around 0.3 in annual growth data.
- The volatility of GDP revisions increases to a small degree with k, underlining the fact that revisions beyond $k = 2$ are non-negligible.
- Consumption revisions show similar variation. The initial release of consumption growth has regularly been under-estimated in recent years: the mean revision is very substantially positive.
- Average revisions to non-durable consumption are fairly close to zero, but this masks the substantial magnitude of such revisions. The standard error is around 0.9 in annualized quarterly data, or almost twice the comparable GDP or total consumption standard errors. For annual growth of non-durables consumption, the standard error is comparable with those of the other two series.
- Overall, the revisions to these GDP components tend to be more substantial than the revisions to GDP itself. Despite the widely-held belief that consumption is relatively smooth, revisions to this series suggests that it is not especially easy to measure, and that uncertainty in measured values is substantial.[3]

Consensus forecast errors, $N_{k,t} - C_t$:

- The mean consensus forecast errors for GDP growth are very close to zero, suggesting unbiasedness.
- The mean forecast error for consumption is substantially positive, reflecting the average positive revision to consumption.
- The standard errors and RMSE are similar for GDP and total consumption, although slightly higher for consumption.
- No quarterly consensus forecasts are produced for non-durable consumption.

[3]There are also particular periods in which which revisions were more pronounced: for example, relatively large revisions occurred for consumption and non-durables in 2002 (whereas GDP was not greatly revised that year), while larger GDP revisions were made in 2001 and 2004.

3.4 Error prediction

If all available information is effectively used when forecasts are made, or when national accounts data are released, then the forecast and measurement errors should be unpredictable. Given that debit card transactions represent a new source of information, we can assess their utility for forecasting and measurement by verifying whether they can explain any part of the observed errors. If they represent statistically significant predictors of the errors, then they should in principle be of use to forecasters and national accountants to reduce the future forecast and measurement errors.

However, there are a number of limitations to our ability to make inferences about predictive content of transactions data. One is related to sample size: we have only seven years of data since Statistics Canada made the change to chain-weighted indices for major national accounts variables such as GDP. Measurement and revision processes before that time are not directly comparable, although it may prove that they have sufficient structure in common to allow us to learn something about the current process. Relatedly, the short period does not permit out-of-sample forecasting experiments, particularly because our consensus forecast data are also available only relatively recently, beginning in 1999. Nonetheless, this period does correspond with one in which the debit card payment mechanism had become a relatively mature technology.

The results that follow, therefore, should be viewed as exploratory and suggestive.

Demers (2006) examines several possible predictors of Canadian data revisions, so we do not replicate an exhaustive search of candidate variables that can predict revisions here. Instead, we use these results to obtain a simple, consistent specification across both forecasting and measurement errors, to compare the value of the debit card transaction information across the various errors that are modeled.

In Tables 2-4 we examine forecasting equations to predict both the consensus forecast errors and the measurement errors characterized above. In addition to debit card transactions we augment our equation with lags of real interest rates, since this variable is in many cases found to provide apparent forecasting power. We also incorporate a lagged error term to capture possible autocorrelation in the error process in a parsimonious way. The general form of the forecasting equation is

$$\epsilon_t = \alpha + \sum_{i=0}^{2} \beta_i D_{t-i} + \sum_{j=1}^{3} \gamma_j \Delta R_{t-j} + \sum_{\ell=1}^{3} \theta_\ell \epsilon_{t-\ell} + u_t \tag{2}$$

where:

- ϵ_t is any one of the measurement or consensus forecast errors described above, and we consider errors for real GDP growth, consumption and non-durables consumption. For the consensus error (1), we focus solely on the initial release errors, since subsequent sources of errors are due solely to data revisions and these are analyzed separately below. For the measurement errors $N_{k,t} - N_{1,t}$, we consider revisions associated with the second, third or fourth releases, so k is set to 2, 3 or 4.

– D_t is the de-trended debit card series discussed in Section 2.2. Note that debit cards enter the equation contemporaneously, reflecting the fact that in practice this data series is available before the national accounts series for the same period. For example, the third quarter ends on 30 September, and since debit card transactions are available daily, the total transactions for the third quarter would be available to an analyst on 1 October. Meanwhile, the national accounts observation for the third quarter is not released until about 30 November, so an analyst using electronic transactions would be able to "nowcast" third quarter growth a full two months before the actual growth rate is released.
– ΔR_{t-j}, are real short-term interest rates lagged by j quarters. They are included in the equation since they are often found to be statistically significant predictors by Demers (2006), indicating the possibility that forecasters and national accountants may not be fully taking into account the effects of monetary policy actions in their forecasts or estimates. Incorporating potential predictors other than debit transactions provides, of course, a more rigorous test of the utility of the latter.

Estimation results for variants of equation (2) are presented in Tables 2-4 for lag lengths chosen by the Schwarz information criterion (SIC), using the quadratically de-trended debit transaction series. Table 2 record results for quarterly measurement errors $N_{kt} - N_{1t},\ k = 2, 3, 4$, Table 3 for the corresponding annual measurement errors, and Table 4 for the annual consensus forecasts errors $N_{kt} - C_t,\ k = 1, 2, 3, 4$.

Although these are exploratory results, a few points seem noteworthy. First, the specifications chosen by SIC retain debit transactions in 18 of 26 cases, and in a number of these cases debit transactions or their lags show statistically significant effects by conventional tests on the regression parameter, despite the very small sample sizes. The greatest utility of the debit card data appears to arise in predicting quarterly GDP measurement errors; in annual measurement errors there is little statistical evidence of an effect, although again the small sample size implies little power to reject the null of no effect in any event. In annual consensus forecasting errors, there is again some evidence of value of the debit transaction variable despite the very small sample size. As well, a varying but sometimes substantial proportion of the variation of these errors is fitted by the regression specification.

In general, the results are suggestive of potential benefit to statistical agencies from the use of electronic transactions data to improve the initial estimates of some national accounts data, and also of potential benefit to forecasters of incorporating these data into their information sets. We note as well that the addition of further sources of electronic transactions, such as credit card transactions reported on a similar basis, could only improve our ability to forecast key quantities and revisions to them.[4] While

[4]Some credit card transactions are processed on paper, and even electronically-recorded credit card transactions may be posted in the days following the actual transaction; the transaction date is not invariably recorded separately from the data of posting. Debit card transactions, by contrast, are always electronically processed and immediately

these results cannot be based on a sufficiently long period to offer firm conclusions, they are suggestive of substantial information content.

4. High-frequency analysis of selected shocks

Another class of potential application of these data is to examine short-term, even daily, impacts of important events; note again that judging these impacts requires a data source that is recorded precisely, at high frequency, and where the transaction date is known. Correspondingly, our aim in this section is to judge whether any impact of two particular extreme events can be observed through electronic transaction data. To this end we need to account for important predictable effects on transactions, in particular day-of-the-week and holiday effects. The examples used here are two especially important events arising in the post-2000 data.

4.1 September 11 terrorist attacks

The terrorist attacks of September 11 2001 had, of course, little direct impact in Canada apart from the diversion of some flights because of closed U.S. airspace. However, the magnitude and visibility of the attacks suggest a possible disruption of activity well outside directly affected areas.

September 11 2001 was a Tuesday, 8 days after Labour Day. Considerable variation in the daily transaction total is visible in the vicinity of Labour Day, as Figure 5 indicates. Moreover, regular peaks in transactions occur on Fridays and troughs on Sundays. The transactions on 3 September 2001 were slightly over 3 million, well below the typical Monday average for that quarter of over 4 million.

To measure the extent of the drop in transactions on September 11 relative to a forecast value, we standardize the observed transactions around this date as $Z_t = \hat{\sigma}^{-1}(D_t - \overline{D})$, where D_t is the value of debit card transactions at time t, $\overline{D} = \frac{1}{3}\sum_{i=2}^{4} D_{t-7i}$, and the $\hat{\sigma}$ is the standard error.

Note that since transactions regularly vary according to the day of the week, we subtract the mean of observed transactions for that particular day. Furthermore, since a holiday observation occurs shortly prior to 9/11 (i.e. Labour Day), we compute this mean using the data from 2, 3 and 4 weeks prior (i.e. 14, 21 and 28 days before). This standardization is performed for both 2000 and 2001.

In Figure 5 we plot the standardized values for both 2000 and 2001. Given that transactions vary greatly with each day of the week, the comparison between 2001 and the equivalent period in 2000 is made relative to Labour Day: Time t in the graphs represent the 8^{th} day after Labour Day (note that this is the same day of the week in each case, as Labour Day is always a Monday. In 2001 this corresponds to September 11; in 2000, t represents September 12).

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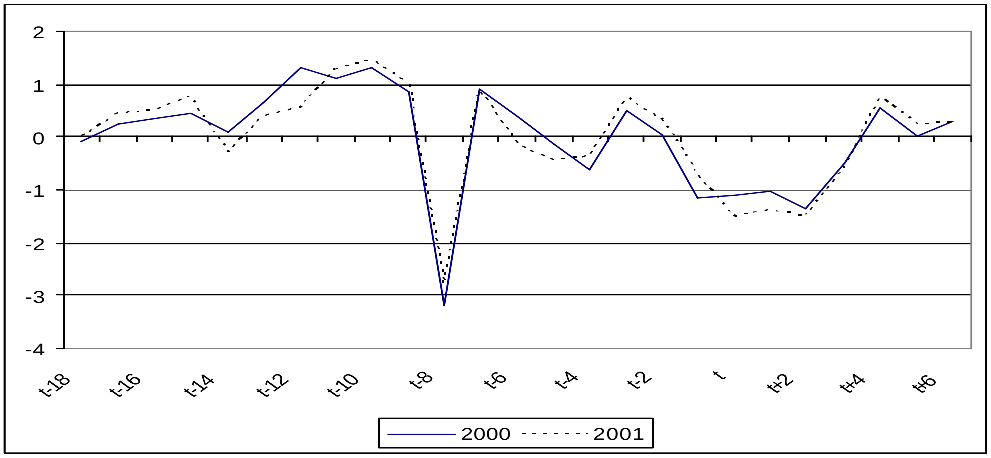
recorded.

Figure 5

Standardized transaction values in the vicinity of September 11 (date t), 2001 and 2000



We observe that the series are very similar for each year. They peak prior to Labour Day (t-8), drop by an equivalent amount on Labour Day, and then follow a similar pattern thereafter. On 9/11 we see that transactions in 2001 were only slightly below their (relative) equivalent 2000 levels. In fact, a similar gap exists around four days prior to Labour Day (t-12), where consumers in 2001 were relatively less active than in 2000. The small relative gap was closed by t+2, indicating that any anomalous drop in debit card transactions on September 11 was back to its (relative) equivalent 2000 levels on September 14. However, this gap is itself well within normal variation.

The difference between the standardized values for 2000 and 2001 in Figure 5 at times t, *t+1* and *t+2* would translate into a point estimate of net loss of 461,000 debit card transactions, or about 10% of a single day's number of transactions in 2001Q3. Nonetheless, the difference between the two years' standardized values is well within one standard error, and indeed the September 11 2001 value is only slightly more than one standard error below the mean. That is, the estimated direct impact of the terrorist attacks in terms of lost or postponed consumption *in Canada* was relatively small in absolute terms, and well within the range of normal variation. While the September 11 attacks no doubt had very substantial effects on economic activity which would be observable in data specific to New York State or, of course, New York City, we can discern little impact in Canadian data.

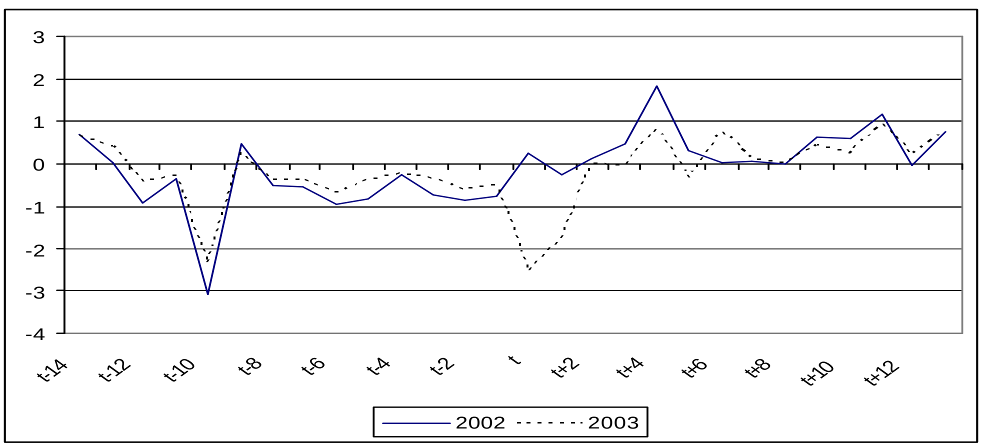
4.2 The blackout of August, 2003

Around 4:00 pm on Thursday August 14, 2003, a power failure affected nearly 50 million households throughout most of Ontario and several U.S. states. Power was gradually restored over the next 48 hours, but the effect of the failure lingered for over a week as businesses and government were urged not to resume normal operations in an effort to conserve energy so as not to place stress on the fragile power grid. For example, many government workers in Ottawa did not return to work until 25 August. This section analyses the impact of the blackout on debit transactions.

Holidays around this period in 2003 were observed on 4 August (Civic Holiday) and 1 September (Labour Day), where reductions in transactions are seen in each case. In the raw transaction data (not recorded here), an unusual change in the series evidently occurs on the first day of the blackout, 14 August. Transactions on this and subsequent days were slightly below the usual values that we typically observe on Thursdays (August 14) and Fridays (August 15).

For comparison in analyzing the impact of the blackout, in Figure 6 we plot standardized transactions, computed as described above, relative to the third quarter of 2002, in which there were no major shocks.

Figure 6
Standardized transaction values in the vicinity of the blackout,
August 14 (date t), 2003 and 2002



Time t in this graph represent the 10^{th} day after the Civic Holiday. In 2003 this corresponds to 14 August; in 2002, t represents 15 August. We observe that the series are very similar for each year; transactions drop sharply on the Civic Holiday, and then follow a similar pattern thereafter. On the day of the blackout we see that transactions in 2003 dropped sharply relative to their equivalent 2002 levels. In terms of magnitude, the transactions on the day of the blackout were similar to those observed on the Civic Holiday. We also observe that the relative gap was largely closed by $t+2$, indicating that following the drop on 14 August and 15 August, debit card transactions returned to their (relative) equivalent 2002 levels on Saturday, 16 August. However, 2003 transactions lingered below their 2002 levels up to 19 August, likely reflecting the fact that normal business activities did not fully resume in some areas for about one week following the blackout.

The difference (of over two standard errors) between the standardized values for 2002 and 2003 in Figure 6 at times t and $t+1$ translates into a net loss of about 1.9 million debit card transactions, or about 28% of a single day's transactions for a typical Thursday or Friday in August of 2003 (the 2003 value is also over 2 standard errors below the mean). Of course, in the absence of electricity some transactions would have been conducted using cash instead of debit cards. However, we surmise that such a substitution of payments methods would have only occurred for a small number of transactions, since many businesses were forced to close during the power outage, and unless households were holding cash at the time of the blackout, cash was difficult to obtain since ATMs were also not functioning.

Furthermore, we observe that since the blackout occurred at 4pm on a Thursday and lasted for most of Friday in many places, it disturbed particularly busy consumption days, which may have contributed to a relatively large impact on consumption. The availability of even higher-frequency data (e.g. hourly basis) would allow us to measure the impact of the blackout on an even finer basis.

5. Conclusion

This paper investigates the usefulness of a type of electronically recorded transaction data for macroeconomic analysis. Since time series of debit card transactions and most other electronic transactions are not publicly available, economic forecasters and national accountants have not incorporated such series into their respective information sets. By assessing the ability of debit cards to explain forecasting errors and data revisions, we are able to consider whether this series has any value for economic analysis and measurement. The evidence we find does suggest that debit card data can potentially lead to improvements in consensus forecasts of GDP growth, and may also help to predict the revisions to GDP. Of course, our ability to make such improved predictions would be expected to improve further with the addition of other electronic data sources; the results from one source should be viewed as suggestive of positive potential, but not as a measure of the magnitude of the total gain (or loss reduction) available.

We also consider the usefulness of electronically recorded data in tracing the very short term economic impacts of important events. Our examples treat the analysis of consumption around September 11 2001, and around the August 2003 electrical blackout. Since no other macroeconomic variables are available at this frequency, analysts have traditionally had difficulty analyzing the direct impacts of such events. We find that the decreased consumption in Canada around September 11 was well within the range of normal variation; for the electrical blackout we find a clear drop in consumption as measured by debit transactions. In either case we note that the debit card data allow a form of analysis not previously possible.

One could in principle further refine our estimates of the economic impacts of these shocks by relying on still higher-frequency (e.g. hourly) transactions data. Similarly, given that larger purchases are often made using credit cards, it could be useful to combine the debit card transactions with credit card transactions in order to provide a richer high-frequency picture of household expenditure habits; such an aggregate could account for larger proportions of observed forecasting and measurement errors in key national account variables.

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Table 1: Descriptive Statistics: Observed Errors

Sample: 2001:1 to 2007:4

Error	National Accounts Variable (*N*)								
	GDP			Consumption			Non-Durables		
	Mean	Std Error	RMSE	Mean	Std Error	RMSE	Mean	Std Error	RMSE
Measurement Errors: Quarterly Annualized Growth Rates									
$N_{2,t} - N_{1,t}$	0.054	0.515	0.508	0.398	0.573	0.689	0.192	0.928	0.931
$N_{3,t} - N_{1,t}$	-0.022	0.553	0.542	0.347	0.509	0.608	0.041	0.838	0.823
$N_{4,t} - N_{1,t}$	-0.116	0.579	0.579	0.355	0.498	0.603	0.042	1.127	1.110
Measurement Errors: Year-over-Year Growth Rates									
$N_{2,t} - N_{1,t}$	-0.027	0.278	0.274	0.113	0.187	0.216	0.057	0.329	0.328
$N_{3,t} - N_{1,t}$	-0.048	0.287	0.285	0.105	0.242	0.260	0.015	0.304	0.298
$N_{4,t} - N_{1,t}$	-0.018	0.313	0.308	0.110	0.315	0.328	-0.012	0.332	0.326
Consensus Errors: Year-over-Year Growth Rates									
$N_{1,t} - C_t$	-0.014	0.407	0.400	0.267	0.506	0.564	N/A	N/A	N/A
$N_{2,t} - C_t$	-0.046	0.411	0.406	0.331	0.451	0.552	N/A	N/A	N/A
$N_{3,t} - C_t$	-0.074	0.427	0.425	0.314	0.422	0.519	N/A	N/A	N/A
$N_{4,t} - C_t$	-0.049	0.442	0.436	0.309	0.467	0.552	N/A	N/A	N/A

Note: RMSE = Root Mean Squared Error

Table 2: Estimated Parameters for the Q/Q Measurement Errors

Sample: 2001:1 to 2007:4

Variable	GDP			Consumption			Non-Durables		
	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$.	$N_{4,t}-N_{1,t}$	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$	$N_{4,t}-N_{1,t}$.	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$	$N_{4,t}-N_{1,t}$.
Constant	0.029 (0.307)	-0.104 (-0.853)	-0.391 (-3.451)	0.557 (4.549)	0.500 (5.001)	0.430 (3.691)	0.318 (2.061)	0.123 (0.647)	0.044 (0.168)
$Debit_t$	-0.003 (-1.507)	-0.009 (-2.884)	-0.013 (-3.609)	0.006 (1.533)	0.003 (0.904)	0.003 (0.808)	0.010 (1.648)	0.007 (1.176)	0.003 (0.371)
$Debit_{t-1}$	--	--	-0.009 (-2.313)	--	--	–	--	--	--
DR_{t-1}	-0.241 (-1.290)	-0.397 (-2.778)	-0.640 (-3.768)	0.320 (2.092)	0.198 (1.545)	0.186 (1.389)	0.847 (2.674)	-0.170 (-0.522)	-0.232 (-0.641)
DR_{t-2}	--	0.441 (2.540)	--	--	--	–	--	--	--
$Error_{t-1}$	-0.276 (-1.365)	0.242 (1.346)	0.197 (1.248)	0.011 (0.071)	-0.233 (-1.682)	-0.030 (-0.180)	0.702 (4.956)	-0.040 (-0.192)	-0.150 (-0.634)
$Error_{t-2}$	--	--	--	-0.345 (-2.947)	--	–	--	--	--
$Error_{t-3}$	--	--	--	0.408 (2.520)	--	–	--	--	--
$\overline{R}^2$	0.11	0.17	0.36	0.27	-0.03	-0.10	0.31	-0.08	-0.13

Note: Debit card growth rate series was detrended using a quadratic trend.

Table 3: Estimated Parameters for the Y/Y Measurement Errors

Sample: 2001:1 to 2007:4

Variable	GDP			Consumption			Non-Durables		
	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$.	$N_{4,t}-N_{1,t}$	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$	$N_{4,t}-N_{1,t}$.	$N_{2,t}-N_{1,t}$	$N_{3,t}-N_{1,t}$	$N_{4,t}-N_{1,t}$.
Constant	-0.053 (-0.942)	-0.067 (-0.912)	-0.042 (-0.515)	0.133 (3.770)	0.084 (1.462)	0.281 (2.100)	0.113 (1.800)	0.052 (0.779)	0.056 (0.843)
$Debit_t$	-0.001 (-0.878)	-0.001 (-0.641)	-0.001 (-0.784)	0.002 (1.637)	-0.000 (-0.023)	0.006 (1.803)	0.004 (1.809)	0.000 (0.345)	0.001 (0.440)
$Debit_{t-1}$	--	--	--	--	--	0.005 (1.772)	--	--	--
DR_{t-1}	-0.075 (-0.847)	-0.200 (-1.600)	-0.200 (-1.573)	0.069 (1.106)	0.108 (1.850)	-0.073 (-0.869)	0.246 (1.623)	0.150 (2.009)	0.068 (0.766)
DR_{t-2}	--	--	--	--	--	–	--	--	0.235 (2.196)
$Error_{t-1}$	-0.342 (-1.692)	0.129 (1.865)	0.159 (1.355)	0.159 (0.855)	0.359 (2.113)	0.722 (5.207)	0.701 (2.517)	0.759 (4.328)	0.612 (4.234)
$Error_{t-2}$	--	--	--	--	--	-0.310 (-3.030)	--	--	--
$\overline{R}^2$	0.04	0.00	-0.01	-0.01	0.03	0.40	0.26	0.24	0.22

Note: Debit card growth rate series was detrended using a quadratic trend.

Table 4: Estimated Parameters for the Y/Y Consensus Errors

Sample: 2001:1 to 2007:4

Variable	GDP				Consumption			
	$N_{1,t}-C_t$	$N_{2,t}-C_t$•	$N_{3,t}-C_t$	$N_{4,t}-C_t$	$N_{1,t}-C_t$	$N_{2,t}-C_t$•	$N_{3,t}-C_t$	$N_{4,t}-C_t$•
Constant	0.046 (0.592)	-0.015 (-0.197)	-0.036 (-0.523)	-0.017 (-0.219)	0.283 (2.109)	0.316 (2.900)	0.213 (2.244)	0.206 (1.891)
$Debit_t$	0.005 (2.171)	0.003 (1.664)	0.004 (1.889)	0.002 (0.875)	0.000 (0.174)	0.001 (0.319)	-0.002 (-0.819)	-0.001 (-0.376)
DR_{t-1}	-0.054 (-0.311)	-0.180 (-0.916)	-0.282 (-1.509)	-0.277 (-1.839)	-0.063 (-0.200)	-0.239 (-1.21)	-0.314 (-2.247)	-0.364 (-2.540)
DR_{t-2}	--	-0.301 (-1.957)	-0.290 (-1.817)	--	--	--	--	--
$Error_{t-1}$	0.283 (1.641)	0.406 (2.865)	0.389 (2.722)	0.418 (2.969)	-0.145 (-0.571)	-0.005 (-0.027)	0.086 (0.698)	0.087 (0.542)
$\bar{R}^2$	0.07	0.29	0.37	0.21	-0.10	-0.06	-0.01	-0.01

Note: Debit card growth rate series was detrended using a quadratic trend