Nowcasting GDP: Electronic Payments, Data Vintages and the Timing of Data Releases

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March 31, 2014

Outline

- - the nowcasting problem for GDP
- - reminder: the standard problems
- - daily payments system data set
- - forecasting models : composite indicator components; model averaging
- - complexities, including data vintages and data release timing
- - summary results: relative rmse's, q/q and y/y, first- and final-release GDP

Nowcasting GDP

- 'nowcasting': forecasting current-quarter GDP: an observation of economic performance in real time
- GDP is released with a two-month lag, so there is a need for forecasts of the current quarterly GDP number, even up to two months after the end of a quarter.
- Current-quarter GDP can therefore be said to be 'nowcasted' for three months during the quarter, and two months after

reminder: the standard problems

- GDP growth forecasting/ nowcasting is exceptionally difficult even by macro- forecast standards
- skill scores are low: beyond horizon one (one quarter in q/q forecasts), skill is not far from zero; some well known model classes routinely perform worse (at least for horizon ≥ 2) than using the unconditional mean
- sample sizes are very small, and only four new points accrue per year; confidence intervals are large
- the data sets are well known; one is inevitably aware of what is in the pseudo-out-of-sample set
- GDP data have substantial measurement error, large standard error of data revisions, data revisions at various dates well into the future

So we try daily payments system data

- data on debit card purchases are available daily (and can be had at even higher frequency, and by postcode, for extreme-events studies for example), and cheque, credit card data are available at business-day frequency
- these provide a high-frequency and well measured way of tracking consumer expenditure throughout the economy; they in principle are available at the beginning of the next business day
- we obtain daily data from Interac (through which all debit transactions pass), the Canadian payments Association, and the Canadian Bankers Association for credit card data. CPA debit data are verified against the independent data from Interac.
- having all of these means of payment allows us in principle to endogenize substitution

Important limitations

- We are projecting ‘small data’ [quarterly GDP measurements] onto these ‘big data’: the quarterly GDP data still constrain the number of out-of-sample evaluations that will be available.
- This is a single country data set. Cross-country panels would alleviate some of these constraints, but would probably require an international agreement among central banks.
- At this point, updating the data set requires a new agreement with the providers

Daily payments system data

- Debit card transaction data: daily sample is Jan 2000 to Dec 2009; we have value and volume. We capture transactions that cross institutions, so approx. 80% of all transactions. 100 transactions per second, 24/7; average value $48.
- Credit card transaction data: value and volume of all transactions involving Visa and MasterCard (approx. 90% of all Canadian credit card transactions); used less frequently than debit cards, but for larger purchases: average transaction value $110.
- Cheques: we have value and volume of all cheques valued under $50,000 that clear between banks. Cheques are used infrequently (<1% of all transactions), but the average value is large: approx. $1100.

Forecasting models

- conventional variables to include in a composite leading indicator (CLI): housing index; employment; stock price index; real narrow money; US CLI (t-1), average work week, new orders for durables (t-2), shipments of finished goods (t-2), furniture and appliance sales (t-2), other durable goods sales (t-2)
- CLI is a standardized average of such variables, and is released about three weeks following month t.
- forecasting model makes y (quarter-over-quarter or y-o-y GDP growth) a function of lagged y, CLI, and payments variables described earlier.
- release dates are given in the following table.
- we examine whether payments variables produce loss reduction

Forecasting models

- the next stage is to incorporate some more sophisticated forecasting technique. We use model averaging (in this case via Hansen 2007) in order to disaggregate the CLI variable into components and examine whether payments variables tend to be included in the more heavily weighted specifications.
- In the model $y = c + W\Theta + \epsilon$, choose a maximum number of regressors to include, $M < N$, and estimate all models with m regressors, $m = \ell, \ell + 1, \dots, M$. The model average estimator is $\hat{\Theta} = \sum_{m=\ell}^{M} \omega_m \hat{\theta}_m$, where ω_m is the weight of model m and $\hat{\theta}_m$ is the parameter vector estimated using m regressors.

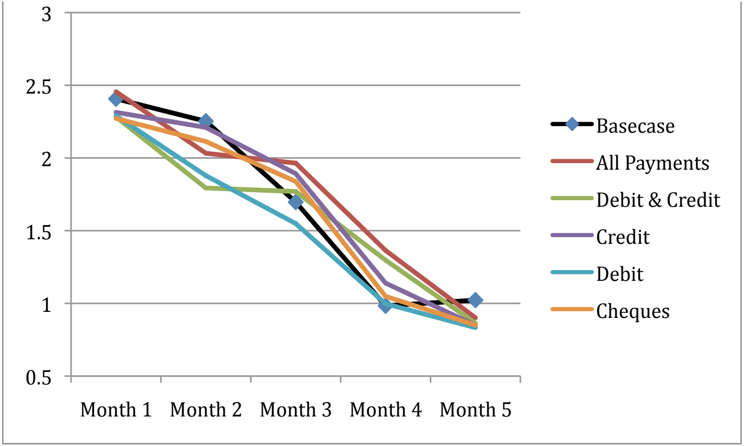
Complexities: data vintages, data release timing

- In order to make a realistic evaluation of the value of an additional data source, we need to reproduce actual forecasting processes as well as possible with and without the new data
- We use vintage data for each quarterly forecast, compliling a new database of monthly GDP revisions, and produce evaluations of the nowcast of first-release and current-vintage GDP data for each quarter in the pseudo-out-of-sample period
- at each nowcast date we use only data available to the nowcaster at that time
- the pseudo-out-of-sample exercise is from 2005Q1 to 2009Q4.
- e.g.: we assume nowcasts for Q3 GDP growth will be produced on July 1, Aug 1, Sept 1 (end Q3), Oct 1 and Nov 1.

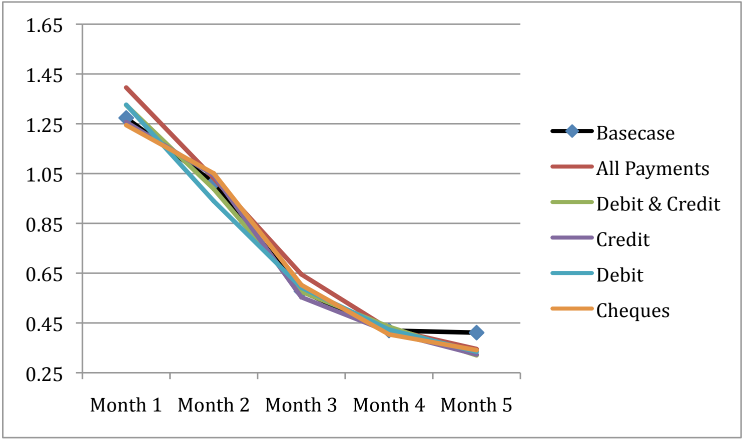
Table 1: Data Release Dates and Nowcasting Equation Specifications

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

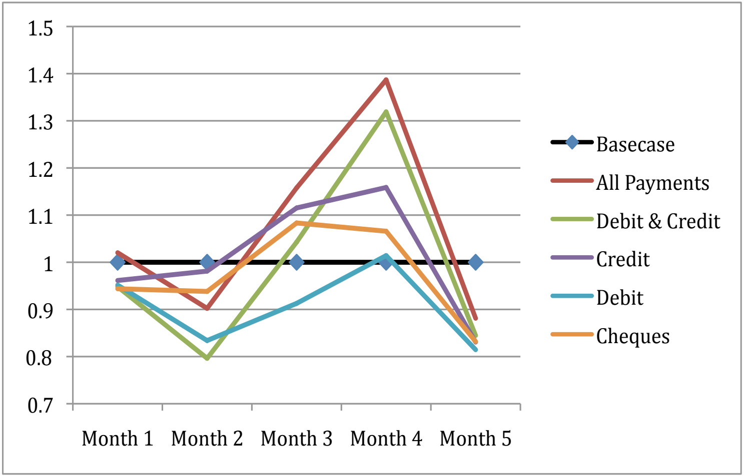
RMSE's, q/q, by month



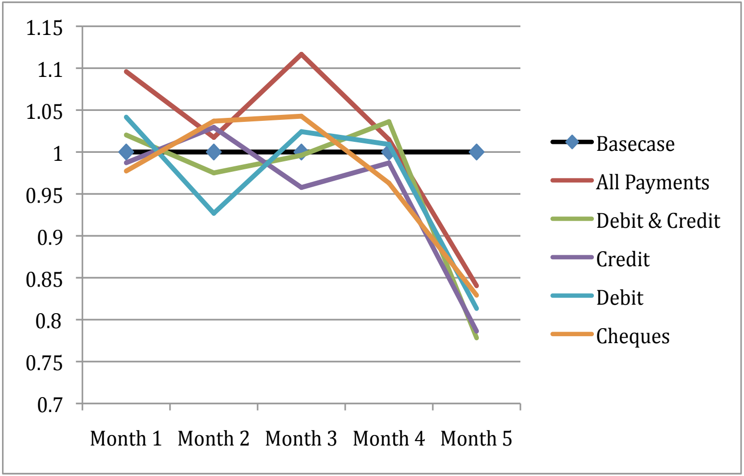
RMSE’s, y/y, by month



Relative RMSE (q/q, first-release)



Relative RMSE (y/y, first-release))



Summary

- Nowcast quality improves markedly with time: rmse's decline by about $\frac{2}{3}$ between months 1 and 5
- Model averaging produces noteworthy ($\sim 10-20\%$) gains at all months. Disaggregating the CLI and using model-averaging on this larger set of variables could produce further gains (we would expect similar results from dimension-reduction methods).
- Use of payments system variables appears to produce some gains at dates immediately preceding the release of national accounts data (months 2 and 5 here), but given available sample sizes, we cannot be highly confident that these effects are genuine