Alternative Economic Indicators

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Published by W.E. Upjohn Institute

Hueng, James.  
Alternative Economic Indicators.  
Project MUSE. muse.jhu.edu/book/82052.

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Getting It Wrong

How Faulty Monetary Statistics Undermine the Fed, the Financial System, and the Economy

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Barnett (2012) documented the degree to which faulty monetary statistics have tended to undermine the Federal Reserve System (the Fed), the financial system, and the economy. That MIT Press book, which brings together nearly a half century of research on that subject, won a Professional and Scholarly Excellence (PROSE) Award for the best book published in economics during 2012, presented by the Association of American Publishers. The research in the book is primarily based on the use of the Divisia monetary aggregates, originated by Barnett (1980) and made available to the public by the Center for Financial Stability (CFS) in New York City. But newer, more sophisticated monetary aggregates are now available from the CFS. The new aggregates incorporate credit card services into the Divisia monetary aggregates, and they distinguish between the demand-side total monetary services consumed and the supply-side inside-money services associated with value added in financial intermediation. This chapter begins the process of updating Barnett (2012) to use the newer data, but with the need for more sophisticated econometric tests in the frequency domain.

Supply-side inside-money aggregates and demand-side total monetary aggregates are not equal, since total demand-side monetary aggregates include outside money not produced as outputs of private financial intermediaries. As economic indicators, they may perform differently in the short run and in the long run. Divisia monetary aggregates, on
the demand side or supply side, can be expected to perform even better when credit-card transaction services are taken into account. In this chapter, we empirically compare credit card–augmented inside-money supply-side Divisia aggregates and total-money demand-side Divisia aggregates. In particular, we compare their correlations with major economic policy targets in the short term and long term. To acquire dynamic performances for time-series data at different frequencies, we transform their time series into the frequency domain using spectral analysis methods. Spectral coherence between the Divisia indexes and major final targets of policy at different frequencies can provide evidence of the role of inside-money supply-side Divisia and total-money demand-side Divisia in the short run and long run.

The original Divisia monetary aggregates measure demand-side monetary services using the economic aggregation and index number theory developed by Barnett (1980). The data are available from the Center for Financial Stability (CFS) in New York City. On the demand side, there is no reason to differentiate among inside money, outside money, regulated services, or shadow banking services. Demanders consume liquidity services supplied by all relevant sources. On the supply side, the manner in which the monetary services are produced is highly relevant to the transmission mechanism of monetary policy and to the indicator value of the resulting service flows.

On the supply side, traditionally, outside money has been measured as the monetary base, supplied by the Federal Reserve as the sum of currency and bank reserves. Inside money has been calculated as the difference between the total-money supply, measured as a simple sum, and outside money. In recent years, that measure of inside money has become conspicuously defective, with M1 inside money often being negative, despite the fact that most of the monetary services in the economy are now produced by private banks as value added in banking and, hence, properly representing inside money.

In recent decades, transaction and liquidity services have been augmented dramatically by the growth of privately supplied unregulated monetary services from bank-supplied credit cards and from the services provided by unregulated shadow banking. We consider inside money using aggregation and index number theory, not simple-sum accounting, and we augment our aggregates with credit-card service flows. We believe that the relationship between inside-money services
on the supply side, total monetary services on the demand side, and final targets of policy can differ at different frequencies, since the transmission mechanism behaves differently in the short run from the long run.

Exploring those extensions of Barnett (2012) would best be done using harmonic analysis. As a first step in that direction, we investigate the properties of the data in the frequency domain using spectral analysis. But that approach, while being the appropriate first step in the intended direction, requires stationary data, which lose relevant information about the dynamics of the economy and of the monetary transmission mechanism. In addition, that approach is heavily sample-size dependent. In subsequent research, we plan to extend this approach to the time-frequency domain using wavelets, in accordance with the approach in Barnett, Ftiti, and Jawadi (2019). This chapter contains our first steps in that direction.

CREDIT CARD–AUGMENTED DIVISIA

Using accounting conventions, credit cards cannot be aggregated with monetary assets, since monetary assets are assets and credit-card balances are liabilities. Accounting conventions do not permit adding liabilities to assets. But aggregation and index number theory aggregate over service flows, regardless of whether produced by assets or liabilities. As shown by Barnett and Su (2020), services of credit cards and of monetary assets can be aggregated using aggregation and index number theory.

These are the definitions of variables used in Barnett and Su’s (2020) model:

\[ R_t = \text{expected yield on the benchmark asset, representing the rate of return on pure capital;} \]

\[ \mathbf{\mu}_t = \text{vector of real balances, } \mu_{it}, \text{ of monetary asset deposit-account type } i \text{ during period } t; \]

\[ \mathbf{\tau}_t = \text{vector of real expenditure volumes, } \tau_{jt}, \text{ with credit-card type } j \text{ for transactions during period } t; \]
\( \mathbf{e}_t = \) vector of expected interest rates, \( e_{it} \), on \( \tau_i \);

\( \mathbf{z}_t = \) vector of rotating real balances, \( \zeta_{jt} \), in credit-card type \( j \) during period \( t \) from transactions in previous periods;

\( \mathbf{c}_t = \) vector of expected interest rates on \( \mathbf{z}_t \);

\( c_t = \) real balances of excess reserves held by the intermediary during period \( t \);

\( \mathbf{L}_t = \) vector of labor quantities receiving expected wage rates, \( \omega_i \), during period \( t \);

\( z_t = \) quantities of other factors of production;

\( c_t = \) price of the factor \( z_t \);

\( k_t = \) reserve requirements, where \( k_{it} \) is the reserve requirement applicable to \( \mu_{it} \), and \( 0 \leq k_{it} \leq 1 \) for all \( I \);

\( R^d_t = \) Federal Reserve expected discount rate;

\( R_t = \min \{ R_t, R^d_t \} \);

\( \gamma_t = \) vector of expected yields paid by the firm on \( i_t \); and

\( p_t^* = \) true cost of living index, used to deflate nominal balances to real balances.

The vector \( \gamma_t \) is defined so that the nominal user-cost price for produced monetary asset \( i_t \) is

\[
\gamma_{it} = p_t^* \left( 1 - k_{it} \right) R_t - \rho_{it} \frac{1}{1 + R_t}.
\]

The vector \( \tilde{\pi}_t \) is defined so that the nominal expected user-cost price for produced credit card services, \( \tau_{jt} \), is

\[
\tilde{\pi}_{jt} = p_t^* \frac{e_{jt} - R_t}{1 + R_t}.
\]

The vector \( \sigma_t \) is defined so that the nominal expected user-cost price for carried-forward rotating credit card debt, \( \zeta_{jt} \), is
\[ \sigma_{jt} = p_t^* \frac{e_{jt} - R_t}{1 + R_t}. \]

The nominal expected user-cost price of excess reserves, \( c_t \), is

\[ \gamma_{0t} = p_t^* \frac{R_t}{1 + R_t}. \]

The corresponding expected real user costs are

\[ \frac{\gamma_t}{p_t^*}, \frac{\tilde{\pi}_t}{p_t^*}, \frac{\sigma_t}{p_t^*}, \text{ and } \frac{\gamma_{0t}}{p_t^*}. \]

Based on the aggregator function existence assumption of technology weakly separable in produced monetary asset service, the Divisia money index for produced inside-money services is acquired by solving the financial intermediary’s decision problem. The result is

\[ \log M_t^* - \log M_{t-1}^* = \sum_i s_i (\log \mu_{it}^* - \log \mu_{it-1}^*) + \sum_j \mu_{jt} (\log \tau_{jt}^* - \log \tau_{jt-1}^*), \]

where \( M_t^* \) = the economic output quantity aggregate for financial firms.

Here, \( s_i = \frac{1}{2} (s_{it} + s_{i,t-1}) \), with \( s_{it} \) and \( u_{jt} \) computed from

\[ s_{it} = \mu_{it} \gamma_{it}^* \left( \mu_{i,t}^* \gamma_{i,t}^* + \pi_{it}^* \right), \text{ and } u_{jt} \text{ is the solution to the constrained revenue maximizing problem:} \]

\[ \text{Max } \mu_{it}^* \gamma_{it}^* + \pi_{it}^* \text{ subject to } f(\mu_t, \tau_t, k_t) = M_t^*. \]

Unlike conventional accounting inside money, the CFS credit card–augmented Divisia inside-money aggregates correlate very well with nominal GDP and can serve the central purposes of inside money, long contemplated in the literature on monetary economics. Further knowledge of its properties remains to be discovered and explored in the frequency domain.

The primary differences between the supply-side measure and the CFS demand-side Divisia monetary aggregates is the supply side’s inclusion of credit card services and exclusion of currency and Treasury bills.
Another difference between the demand-side and the supply-side user-cost formulas for monetary asset services results from the existence of reserve requirements, producing an implicit tax on banks. But in recent years, that tax has been nearly zero because of sweeps, low interest rates, and Federal Reserve payment of interest on reserves.

In this chapter, we begin our empirical exploration of the inside-money and total credit card–augmented Divisia for broad M4 and narrow M1, beginning from July 2007. Moving from DM1 (Divisia Ma) to the higher levels of aggregation incorporates increasing amounts of shadow banking and negotiable money-market security liquidity services, properly weighted.

SPECTRAL ANALYSIS THEORY

For a finite series \( u(j) \) of length \( T = N\Delta t \), here with \( N \) referring to the sample size and \( \Delta t \) referring to the sampling periodicity, the discrete Fourier transform (DFT) \( U(k) \) of \( u(j) \) and its inverse (IDFT) for finite series (see, e.g., Iacobucci [2005]) are

\[
U(k) = \frac{1}{N} \sum_{j=0}^{N-1} u(j) e^{-2\pi ijk/N}
\]

and

\[
u(j) = \sum_{k=-[N/2]}^{[N-1]/2} U(k) e^{2\pi ijk/N},
\]

where \( u_k = \frac{k}{N\Delta t} \) is the frequency and \( T = N\Delta t \) is the time. In our power spectrum for real data in later parts of the paper, the label for frequency domain is \( v_k \), and the period should be \( 1/v_k \). The power spectrum is given by

\[
P_u(k) = |U(k)|^2.
\]

An estimator for the power spectrum is given by Schuster’s Periodogram:
\[ P_u(k) = \Delta t \sum_{J=(N-1)}^{N-1} \gamma_{uu}(J) \cos \frac{2\pi Jk}{N} , \]

where \( \gamma_{uu}(J) = \gamma_{uu}(-J) = N^{-1} \sum_{j=(N-J)}^{N-J} (u(j) - \bar{u})(u(j+J) - \bar{u}) \) is the standard sample estimation at lag \( J \) of the autocovariance function.

To build a spectral estimator, which is more stable—i.e., it has a smaller variance than \( P_u(k) \)—we turn to the technique of windowing. This technique is employed both in time and in frequency domain to smooth all abrupt variations and to minimize the spurious fluctuations generated in time as a series is truncated. The smoothed spectrum is given by

\[ \hat{S}_u(k) = \Delta t \sum_{J=(N-1)}^{N-1} \omega_M(J) \gamma_{uu}(J) \cos \frac{2\pi Jk}{N} , \]

where the autocovariance function is weighted by the lag window \( \omega(j) \) of width \( M \). It can be shown that this is equivalent to splitting the series in \( N/M \) subseries of length \( M \), computing their spectra, and taking their mean with the spectral window \( W_M(k) \) of width \( M = M - 1 \).

For two time series, \( u_1(j) \) and \( u_2(j) \), with cross covariance \( \gamma_{12}(J) = \gamma_{12}(-J) \), the cross spectrum is

\[ \hat{S}_{12}(k) = \Delta t \sum_{J=(N-1)}^{N-1} \omega(J) \gamma_{12}(J) e^{-i\frac{2\pi Jk}{N}} = \hat{C}_{12}(k) - i\hat{Q}_{12}(k) . \]

Here, the real part \( \hat{C}_{12}(j) \) is the cospectrum, and the imaginary part is the \( i\hat{Q}_{12}(j) \) quadrature spectrum. The coherency spectrum (correlation coefficient) is

\[ \hat{K}_{12}(k) = \frac{\left| \hat{S}_{12}(k) \right|}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} = \frac{\sqrt{\hat{C}_{12}(k)^2 + \hat{Q}_{12}(k)^2}}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} . \]

The phase spectrum (time lag) is

\[ \hat{\Phi}_{12}(k) = \arctan\left( \frac{-\hat{Q}_{12}(k)}{\hat{C}_{12}(k)} \right) . \]
which measures the phase difference between the frequency components of the two series: 1) the number of leads (> 0) or 2) the number of lags (< 0) of $u_1(j)$ on $u_2(j)$.

**DATA**

Regarding the data sources, see Barnett and Su (2020). The credit card transaction services can be measured by the transaction volumes summed over four sources: Visa, Mastercard, American Express, and Discover. The credit-card-augmented Divisia aggregate does not apply to debit cards, nor to store cards, nor to charge cards not providing a line of credit. The model identifies credit card services as sources of value added in banking and therefore outputs of financial intermediation, since those credit card accounts provide deferred payment services. Cash and checking accounts do not provide that service. Debit cards do not, either. The services of debit cards are similar to the services of checking accounts, which are already included as services of demand deposit accounts but are not the source of value added we identify as credit card services.

Store cards are not outputs of financial intermediation, since they are maintained by the stores that supply the purchased products. In addition, the connection between store cards and those products sold by the stores is inconsistent with the assumption of blockwise weak separability of financial services and consumer goods on the demand side, since these cards can be used only to purchase the goods sold by the store. Charge cards that do not provide a line of credit are rarely provided by banks, and they are now largely limited to store cards.

**SPECTRAL ANALYSIS RESULTS**

The year-over-year growth rate for credit card–augmented inside-money and total-money Divisia are provided on the website of the Center of Financial Stability (CFS), dated from July 2007 to October 2018; the U.S. unemployment rate and CPI (consumer price index) are
provided by the Bureau of Labor Statistics; and the U.S. inflation rate, along with inflation rates internationally, is provided by statbureau.org from July 2007 to April 2018. The total sample size is \( N = 136 \), but 131 for the inflation rate.

All data are monthly data, corresponding to periodicity of \( \Delta t = \) one month. All time series data were detrended when spectrum estimated. Here we chose modified Daniell smoothers as the smoothing function, with moving averages giving half weight to the end values. The smooth width \( M = 8 \) determines the trade-off between bias and variance for a fixed sample size. The larger the value of \( M \), the smaller the variance of the estimated spectrum at a given frequency, but the larger the bias. To get a smoothed estimated spectrum without losing excessive information, we set \( M = 8 \).

Since the original value of the year-over-year growth rate of Divisia index is small, the power spectrum remains small after estimation. However, the periodic properties for coherence between inside-money Divisia and total-money Divisia, and with unemployment rate, inflation rate, and CPI index, are clear.

In the plots below, we have sample size \( N = 136 \) with an 11-year time range, from 2007 to 2018. Frequency domain results, with the frequency set at \( v_k = 0.1, 0.2, 0.3, 0.4, 0.5 \), correspond to periods of \( 1/v_k = 10.0, 5.0, 3.3, 2.5, \) and 2.0 months, respectively. Although there is high correlation between inside-money and total-money Divisia, their behavior displayed differently at low frequencies over a long period. (See frequency of less than 0.1 with period exceeding 10 months.) Total demand-side money has a high coherency with the main economic indicators.

In the plots for the broad M4 level aggregates, M4AI denotes the inside-money Divisia M4 augmented with credit card services. M4A denotes the total Divisia M4 augmented by credit card services. Figure 2.1 displays the relationship between the total Divisia demand-side aggregate and the supply-side inside-money Divisia aggregate. The first plot displays their power spectrum. The second plot provides the squared coherency, measuring correlation between the two aggregates at different frequencies. The blue dashed lines above and below the coherency plot provide the 95 percent confidence band around the coherency plot. The third plot provides the phase spectrum and its confidence region.
Figure 2.1 Inside DM4 (supply-side) and Total DM4 (demand-side)

SOURCE: Center for Financial Stability.

Figure 2.2 provides the analogous results relating the broad monetary aggregates to the unemployment rate, while Figure 2.3 provides the results relating the monetary aggregates to the inflation rate and Figure 2.4 provides the results relating the aggregates to the CPI level at different frequencies.

In Figures 2.5–2.8, we similarly consider the Divisia index for the narrow M1 aggregate. Moving from M4 to the lower levels of aggregation incorporates decreasing amounts of shadow banking and negotiable money-market security liquidity services. The periodic behavior differences become less significant.

In Figure 2.9, we explore the relationship between unemployment and inflation and thereby the frequency properties of the Phillips curve. The cross correlation, ACF (auto-correlation function) in Figure 2.9, between the unemployment rate and inflation rate is displayed under different numbers of lag. Since the sampling periodicity is monthly, the correlation will be significantly positive only when the lag or lead
between the two indicators is more than 12 months. Also, there are phase differences under different frequencies or periods. As a result, it is not surprising that Divisia growth rates have different coherences with these two indicators.

**PREVIOUS RESULTS**

As this research advances, it will be relevant to compare with prior results that appeared in Barnett (2012) and Barnett and Chauvet (2011), but with the newer augmented aggregates now available from the CFS. Examples from the earlier research include the following figures.

Figure 2.10 displays the broadest Divisia monetary aggregate available from the St. Louis Federal Reserve Bank over a period of 40 years. The figure clearly displays the aggregate’s correlation with the business
Figure 2.3 DM4 and Inflation Rate

![Chart showing smoothed periodogram and squared coherency for in_inf and to_inf series.](chart.png)


cycle and its predictive ability relative to the Great Recession, which began immediately after the end of that figure’s time period.

Figure 2.11 displays M1 inside money computed in the conventional manner as total-money supply minus outside money. The M1 aggregate used in that computation is the Federal Reserve Board’s measure using simple sum aggregation without sweep adjustment. The only available measure of outside money provided by the Federal Reserve is the monetary base. In that figure, the monetary base was acquired from the St. Louis Federal Reserve Bank’s FRED database. Observe that inside money, by that measure, became negative during a period of time when most monetary services in the economy were provided as inside money by privately owned banks and other privately owned financial intermediaries. The error has two sources: 1) simple-sum M1 is biased downward by the Federal Reserve’s failure to sweep adjust its component data, and 2) the Federal Reserve’s measure of the mon-
Figure 2.4 DM4 and CPI


etary base has become an upwardly biased measure of outside money in recent years as a result of the Federal Reserve’s nonstandard policies.

Figure 2.12 displays nonborrowed reserves as reported by the Federal Reserve Board. Nonborrowed reserves were the instrument of monetary policy adopted by Fed chairman Paul Volcker during the three-year period of the “monetarist experiment.” Observe the period during which nonborrowed reserves became negative. That result is a contradiction in terms, since borrowed reserves, by definition, cannot exceed total reserves. The Federal Reserve’s accounting error, producing that impossible result, occurs because it is including within borrowed reserves some bank borrowing not held as reserves.

Figure 2.13 displays the results of the Taylor rule, as provided by the St. Louis Fed’s FRED database. The figure shows the target range for the Taylor rule and the actual path of the federal funds rate. Clearly
Figure 2.5 Inside DM1 (supply-side) and Total DM1 (demand-side)

SOURCE: Center for Financial Stability.

the federal funds rate was below the target range for three successive years, casting doubt on the policy relevance of the interest rate target.

CONCLUSION

In this chapter, we begin our research on updating the results in Barnett (2012) to use the more sophisticated Divisia monetary aggregates recently available from the Center for Financial Stability. Those aggregates are extended to include credit card services and to distinguish demand-side total consumed monetary services from supply-side inside monetary services associated with value added in banking. Since
the transmission mechanism has lags resulting in different correlations with final targets in the long run versus the short run, we introduce into this literature tests in the frequency domain.

To acquire dynamic performances for time series data at different frequencies, we transform the time series into the frequency domain using spectral analysis methods. As the sample size becomes larger, more significant results will become available from data covering a complete business cycle. Although this approach is an appropriate first step in this direction, conversion to the frequency domain requires stationarity. However, such stationary data lose much relevant information about the economy. In subsequent research, we shall investigate nonstationary data with wavelet methodology in the time-frequency domain, following the approach of Barnett, Ftiti, and Jawadi (2019).
Figure 2.7 DM1 and Inflation Rate

Figure 2.8 DM1 and CPI

Figure 2.9 Possible Explanation of Phillips Curve


Figure 2.10 Year-over-Year Growth Rates of the Broadest Available Divisia Monetary Aggregate during 40 Years

Figure 2.11  M1 Inside Money, Computed as Federal Reserve Simple Sum M1 Minus St. Louis Federal Reserve Bank Monetary Base (outside money)

SOURCE: St. Louis Federal Reserve Bank’s FRED Database.

Figure 2.12  Nonborrowed Reserves

SOURCE: Board of Governors of the Federal Reserve System.
Figure 2.13 Taylor Rule Federal Funds Rate


References