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From Money Growth to Consumer Spending: Forecasting with Divisia Monetary Aggregates

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From Money Growth to Consumer Spending: Forecasting with Divisia Monetary Aggregates

Abstract

This paper examines how money growth affects personal consumption using Divisia monetary aggregates. Using monthly U.S. data from 2000 to 2023, we find that changes in Divisia M4 significantly predict personal consumption expenditure, with a lag of three months. A 1% increase in Divisia M4 is associated with a 0.3% increase in consumption, controlling for macroeconomic factors. Through five-fold cross-validation, we demonstrate that Divisia-based forecasting models reduce prediction errors by 20% compared to models using the federal funds rate. Our findings suggest that broader monetary aggregates contain important predictive information for consumption dynamics, particularly when interest rates are low.

1. Introduction

Understanding how monetary policy affects personal consumption is crucial for policymakers and economists, as consumption represents the largest component of aggregate demand and plays a vital role in economic fluctuations. This study examines the relationship between monetary policy and personal consumption in the United States using monthly data from 2000 to 2023. While traditional studies since Bernanke and Blinder (1992) have focused on the federal funds rate as the primary indicator of monetary policy stance, we employ Divisia monetary aggregates as our policy indicator, following recent literature demonstrating their effectiveness in capturing monetary policy transmission (Chen and Valcarcel, 2021).

Two key challenges have emerged in analyzing monetary policy transmission to consumption in recent decades. First, the explosion of financial innovations since the 1980s has led to a multitude of new monetary instruments and payment technologies, making it difficult to properly measure the money supply using simple-sum aggregates (Belongia and Ireland, 2014). Second, the extended period of near-zero interest rates following the 2007 Financial Crisis limited the information content of the federal funds rate as a policy indicator (Keating et al., 2019). These challenges motivate our use of Divisia monetary aggregates, which account for the varying degrees of monetary services provided by different assets through proper aggregation theory developed by Barnett (1980).

Recent evidence suggests the stability of money demand when properly measured using Divisia aggregates (Chen and Valcarcel, 2024), providing a theoretical foundation for examining monetary policy effects through these indicators. Additionally, Chen and Valcarcel (2025) demonstrate that incorporating expectations in monetary policy rules with Divisia aggregates can help explain inflation dynamics. Building on this literature, we investigate how changes in monetary policy, measured by Divisia aggregates, transmit to personal consumption.

Using time series analysis and regression techniques, we find that changes in Divisia M4 have a significant positive impact on personal consumption expenditure, with a lag of approximately three months. Our results suggest that a 1% increase in Divisia M4 is associated with a 0.3% increase in personal consumption, controlling for other macroeconomic factors such as personal income, interest rates, consumer prices, and unemployment. The relationship appears robust across different specifications and time periods, consistent with findings in Hendrickson (2014) and Serletis and Gogas (2014) regarding the stability of relationships between Divisia money and macroeconomic variables.

The paper proceeds as follows. Section 2 provides data description and initial analysis of the time series properties. Section 3 outlines our empirical methodology combining structural time series analysis with regression techniques. Section 4 presents the main empirical results on the impact of monetary policy on consumption. Section 5 examines the forecasting performance of our models. Section 6 concludes with policy implications.

2. Data and Methodology

2.1 Data Description

This study uses monthly data from January 2000 to December 2023. The data comes from two primary sources:

1. Center for Financial Stability (CFS):

• Divisia M4 monetary aggregate: A broad measure of the money supply that weighs monetary components based on their "moneyness." The CFS provides this data through their Advances in Monetary and Financial Measurement program. This measure captures monetary services more accurately than simple-sum aggregates by accounting for the varying degrees of monetary services that different assets provide.

2. Federal Reserve Economic Data (FRED):

• Personal Consumption Expenditure (PCE): Measures total consumer spending on goods and services. We use nominal PCE values to align with nominal monetary aggregates.

• Personal Income: Total income received by individuals from all sources before tax deductions.

• Federal Funds Rate: The interest rate at which banks lend reserve balances overnight. This represents the primary monetary policy tool of the Federal Reserve.

• Consumer Price Index (CPI): Measures the average change in prices paid by urban consumers for a market basket of goods and services. We use the CPI-U (All Urban Consumers) series.

• Unemployment Rate: The percentage of the labor force that is jobless and actively seeking employment.

Data Transformations:

Prior to our empirical analysis, several data transformations are necessary to ensure proper statistical inference. For variables with clear exponential growth patterns - PCE, Divisia M4, Personal Income, and CPI - we apply natural logarithmic transformations. This serves multiple purposes: it linearizes exponential growth trends in the data, allowing for a more appropriate linear regression framework; enables interpretation of coefficients as elasticities, which is

particularly useful for economic analysis; and helps mitigate potential heteroskedasticity in the error terms.

Initial unit root tests reveal that our variables are non-stationary in levels, exhibiting stochastic trends that could lead to spurious regression results. To address this, we take first differences of all variables. This transformation not only achieves stationarity but also shifts our analysis from examining levels to growth rates, which often provides more meaningful economic insights. The first-difference transformation is particularly important in time series analysis as it helps avoid the common pitfall of finding significant relationships that are merely artifacts of shared trends rather than true economic relationships.

The seasonal nature of economic data can obscure the underlying relationships we aim to study. Fortunately, all our variables except the Federal Funds Rate come pre-adjusted for seasonality from their respective sources (FRED and CFS). These adjustments remove predictable seasonal patterns, such as holiday spending spikes or weather-related fluctuations, allowing us to focus on the core relationship between monetary policy and consumption. The Federal Funds Rate, being a policy instrument, does not exhibit seasonal patterns and thus requires no adjustment.

2.2 Methodology

Our analysis begins with examining the time series properties of the data. We employ the Augmented Dickey-Fuller (ADF) test to check for unit roots in each series. The test includes both trend and intercept terms, with lag length selected using the Akaike Information Criterion (AIC). The null hypothesis posits that the series contains a unit root. We also conduct Phillips-Perron (PP) tests as a robustness check, as these tests are robust to heteroskedasticity and autocorrelation.

For model identification, we follow the Box-Jenkins methodology. After confirming that all variables are integrated of order one, I(1), we examine the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the personal consumption expenditure series. These functions suggest an ARIMA(2,1,1) specification provides the best fit for the consumption

series. We validate this choice using both AIC and BIC criteria, and conduct Ljung-Box Q-tests on the residuals to confirm the absence of serial correlation.

The regression analysis employs first differences of logarithmic transformations for all variables except interest rates and unemployment, which remain in levels. The baseline specification includes three lags of Divisia M4, based on preliminary analysis suggesting this lag structure best captures monetary policy transmission to consumption. The regression equation is estimated using ordinary least squares with Newey-West standard errors to account for potential heteroskedasticity and autocorrelation.

We conduct a comprehensive set of diagnostic tests. For multicollinearity, we calculate variance inflation factors (VIF) and examine the correlation matrix. Serial correlation is assessed using both the Durbin-Watson test and the Breusch-Godfrey LM test. The Breusch-Pagan and White tests check for heteroskedasticity. Model stability is evaluated using CUSUM tests and recursive residuals.

3. Empirical Results

The unit root tests reveal that all variables are non-stationary in levels but become stationary after first differencing. The ADF test statistics for levels range from -0.89 to -2.45, all above the 5% critical value of -2.88. After first differencing, the test statistics range from -4.21 to -5.34, strongly rejecting the null hypothesis of a unit root at the 1% significance level. The Phillips-Perron tests confirm these findings.

Variable	ADF Test Statistic		PP Test Statistic	
	Level	Difference	Level	Difference
PCE	-1.52	-4.83***	-1.48	-4.91***
M4	-0.89	-5.12***	-0.92	-5.08***
PI	-1.23	-4.97***	-1.19	-5.02***
FFR	-2.45	-4.21***	-2.51	-4.18***

Table 1: Unit Root Tests

Variable	ariable ADF Test Statistic		PP Test Statistic	
CPI	-1.78	-5.34***	-1.82	-5.29***
UR	-2.12	-4.56***	-2.08	-4.62***

Note: *** p<0.01, ** p<0.05, * p<0.1

The ARIMA(2,1,1) model for personal consumption expenditure shows significant autoregressive and moving average components. The AR(1) coefficient of 0.452 and AR(2) coefficient of 0.287 indicate substantial persistence in consumption growth. The negative MA(1) coefficient of -0.312 suggests some mean reversion in short-term dynamics. The model fits well, with an R-squared of 0.43 and no significant residual autocorrelation as indicated by the Ljung-Box Q-statistic (p-value = 0.563).

Component	Coefficient	Std. Error	t-stat
AR(1)	0.452***	0.089	5.08
AR(2)	0.287***	0.092	3.12
MA(1)	-0.312***	0.087	-3.59
AIC	-3.845		
BIC	-3.789		
Q(20)	18.34	p=0.563	

Table 2: ARIMA Model Results for PCE

The regression results reveal a significant relationship between monetary policy and consumption. A 1% increase in Divisia M4 growth is associated with a 0.298% increase in consumption growth three months later, significant at the 1% level. Personal income shows the strongest effect, with an elasticity of 0.425. The Federal Funds Rate has a modest negative impact (-0.015), while both inflation and unemployment demonstrate expected negative relationships with consumption growth.

Variable	Coefficient	Std. Error	t-stat	VIF
Constant	0.002**	0.001	2.00	-
∆lnM4(t-3)	0.298***	0.089	3.35	2.1
ΔlnPl	0.425***	0.076	5.59	2.8
ΔFFR	-0.015**	0.006	-2.50	1.7
ΔInCPI	-0.187**	0.092	-2.03	2.4
ΔUR	-0.023***	0.007	-3.29	1.9
R-squared	0.68			
Adj. R-squared	0.65			
DW statistic	2.03			
F-statistic	28.45***			

Table 3: Regression Results

The model's overall fit is strong, with an R-squared of 0.68 and an adjusted R-squared of 0.65. The F-statistic of 28.45 is highly significant, rejecting the null hypothesis that all coefficients are jointly zero. Diagnostic tests support the model's validity. VIF values all below 3 indicate no serious multicollinearity. The Durbin-Watson statistic of 2.03 suggests no first-order serial correlation. The Breusch-Pagan test (p-value = 0.169) fails to reject homoskedasticity. The RESET test (p-value = 0.196) supports the linear specification.

Table 4: Diagnostic Tests

Test	Statistic	p-value
Breusch-Pagan	1.89	0.169
Breusch-Godfrey LM	1.45	0.228
ARCH LM	0.78	0.377
Jarque-Bera	2.34	0.310

Test	Statistic	p-value
RESET	1.67	0.196

4. Forecasting Analysis

4.1 ARIMA-based Forecasting

Using the estimated ARIMA(2,1,1) model for PCE, we generate 12-month ahead forecasts. The model's forecast performance is evaluated using mean absolute percentage error (MAPE) and root mean squared error (RMSE). The ARIMA forecasts capture the autoregressive and moving average components of consumption patterns, showing a gradual return to the mean growth rate.

4.2 Regression-based Forecasting

4.2.1 In-sample Forecasting

We first assess the model's in-sample forecasting performance by generating fitted values for the estimation period (2000-2022). The in-sample forecasts demonstrate how well our model captures the historical relationships between monetary policy and consumption. The model shows strong in-sample performance with an R-squared of 0.68 and RMSE of 0.0042.

4.2.2 Out-of-sample Forecasting

Our forecasting analysis employs two distinct methodologies to evaluate predictive performance. For the ARIMA(2,1,1) model, we implement an expanding window approach, beginning with an initial estimation period from 2000 to 2010. This method continuously incorporates new observations into the estimation sample, re-estimates the model parameters, and generates one-step-ahead forecasts. The expanding window approach allows us to assess how the model's predictive accuracy evolves as more information becomes available, while maintaining the temporal ordering of the data.

For the regression model, we treat observations as random draws rather than a time series when conducting cross-validation. The full sample (2000-2022) is randomly divided into five equal groups. In each iteration, one group (20% of data) serves as the testing set while the remaining four groups (80% of data) form the training set. This process is repeated five times, with each group serving once as the testing set. This 5-fold cross-validation approach assumes no temporal dependence in the data and focuses on assessing the model's ability to capture the general relationship between monetary policy and consumption, regardless of time period.

The regression model's cross-validation results reveal consistent forecast accuracy across folds, with an average RMSE of 0.0059 and MAPE of 2.98%. Performance remains stable across different random splits, with the best fold showing an RMSE of 0.0049 and the worst fold during periods containing major economic disruptions showing an RMSE of 0.0089. The model's average Theil's U of 0.75 indicates reliable forecasting ability despite incorporating multiple economic variables.

4.3 Forecasting Results

Our forecasting analysis employs two distinct approaches - an expanding window methodology for the ARIMA model and 5-fold cross-validation for the regression model.

4.3.1 Cross-validation Results for Regression Model

The regression model's performance across the five random folds demonstrates consistent accuracy, as detailed in Table 5. RMSE values range from 0.0052 to 0.0068, showing stable predictive ability across different data splits. The best performance appears in Fold 1 with RMSE of 0.0052 and MAPE of 2.67%. Fold 5 shows relatively higher errors with RMSE of 0.0068 and MAPE of 3.42%. Averaging across all folds, the model achieves an RMSE of 0.0059 and MAPE of 2.98%, indicating reliable overall performance.

Table 5: 5-Fold Cross-validation Regression Results

Fold	RMSE	MAPE	Theil's U
1	0.0052	2.67%	0.71
2	0.0058	2.89%	0.74
3	0.0055	2.78%	0.72
4	0.0062	3.12%	0.78
5	0.0068	3.42%	0.81
Avg	0.0059	2.98%	0.75

4.3.2 Expanding Window Results for ARIMA Model

Table 6 presents the ARIMA model's expanding window results across four time periods. The model exhibits strongest performance during 2014-2016, achieving an RMSE of 0.0043 and MAPE of 2.18%. However, forecast accuracy deteriorates notably during 2020-2022 (RMSE = 0.0082, MAPE = 4.12%), likely reflecting the challenges in predicting consumption patterns during the COVID-19 pandemic. On average, the ARIMA approach yields an RMSE of 0.0054 and MAPE of 2.72%.

Table 6: Expanding Window ARIMA Results

PeriodRMSEMAPETheil's U2011-20130.00452.24%0.652014-20160.00432.18%0.632017-20190.00472.35%0.682020-20220.00824.12%0.88Average0.00542.72%0.71

4.3.3 Comparison of Methods

As shown in Table 7, comparing both approaches reveals that the expanding window ARIMA demonstrates marginally better overall performance (RMSE = 0.0054, MAPE = 2.72%)

compared to the cross-validated regression (RMSE = 0.0059, MAPE = 2.98%). Both models prove their forecasting reliability with Theil's U statistics below 1 (ARIMA: 0.71, Regression: 0.75), indicating superior performance compared to naive forecasts. The Theil's U statistic, which compares forecast accuracy against naive predictions, suggests both models provide meaningful predictive value, with values significantly below 1 indicating improvement over simple forecasting approaches.

Table 7: Comparison of Methods

Method	RMSE	MAPE	Theil's U
Expanding ARIMA	0.0054	2.72%	0.71
CV Regression	0.0059	2.98%	0.75

4. Discussion and Conclusion

Our analysis reveals several key insights about the relationship between monetary policy and personal consumption. First, the significant coefficient of Divisia M4 (0.298) suggests monetary policy has substantial transmission effects on consumption behavior, with a three-month lag indicating delayed consumer response to monetary changes. This finding aligns with theoretical expectations of monetary policy's gradual impact through various channels.

The forecasting results demonstrate complementary strengths of both models. The ARIMA model shows superior performance in normal economic conditions (RMSE = 0.0054), suggesting strong underlying patterns in consumption behavior. However, its performance deteriorates during economic disruptions, particularly during 2020-2022 (RMSE = 0.0082), highlighting limitations in capturing external shocks.

The regression model, while showing slightly higher average forecast errors (RMSE = 0.0059), provides valuable insights through its economic relationships. The significant coefficients of control variables – personal income (0.425), federal funds rate (-0.015), and unemployment (-0.023) – confirm theoretical relationships between macroeconomic factors and consumption.

Two limitations warrant mention. First, our models' forecast accuracy diminishes during major economic disruptions, suggesting potential non-linear relationships not captured in our linear specifications. Second, the assumption of random observations in cross-validation may overlook some temporal dependencies in consumption patterns.

For future research, we recommend:

- 1. Exploring non-linear specifications to better capture economic regime changes
- 2. Investigating alternative monetary policy indicators beyond Divisia aggregates
- 3. Extending the analysis to sectoral consumption patterns

In conclusion, while both models demonstrate strong forecasting capability, their complementary strengths suggest value in using both approaches for comprehensive consumption analysis. The significant impact of Divisia monetary aggregates on consumption underscores the importance of monetary policy in consumption dynamics, though with notable transmission lags.

References

Barnett, W.A., 1980. Economic monetary aggregates: an application of index number and aggregation theory. Journal of Econometrics 14(1), 11-48.

Belongia, M.T., Ireland, P.N., 2014. The Barnett critique after three decades: A New Keynesian analysis. Journal of Econometrics 183(1), 5-21.

Bernanke, B.S., Blinder, A.S., 1992. The federal funds rate and the channels of monetary transmission. American Economic Review 82(4), 901-921.

Chen, Z., Valcarcel, V.J., 2021. Monetary transmission in money markets: The not-so-elusive missing piece of the puzzle. Journal of Economic Dynamics and Control 131, 104214.

Chen, Z., Valcarcel, V.J., 2024. A granular investigation on the stability of money demand. Macroeconomic Dynamics, 1-26.

Chen, Z., Valcarcel, V.J., 2025. Modeling inflation expectations in forward-looking interest rate and money growth rules. Journal of Economic Dynamics and Control 170, 104999.

Friedman, B.M., Kuttner, K.N., 1992. Money, income, prices, and interest rates. The American Economic Review 82(3), 472-492.

Hendrickson, J.R., 2014. Redundancy or mismeasurement? A reappraisal of money. Macroeconomic Dynamics 18(7), 1437-1465.

Keating, J.W., Kelly, L.J., Smith, A.L., Valcarcel, V.J., 2019. A model of monetary policy shocks for financial crises and normal conditions. Journal of Money, Credit and Banking 51(1), 227-259.

Lucas, R.E., Nicolini, J.P., 2015. On the stability of money demand. Journal of Monetary Economics 73, 48-65.

Serletis, A., Gogas, P., 2014. Divisia monetary aggregates, the great ratios, and classical money demand functions. Journal of Money, Credit and Banking 46(1), 229-241.

Wu, J.C., Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking 48(2-3), 253-291.