

Table of Contents

INTRODUCTION	2
THEORETICAL CONSIDERATIONS	3
REPLICATING THE EVIDENCE	5
THE EXTENSION: ADDING INFLATION EXPECTATIONS	8
CONCLUSION	10
REFERENCES	10
APPENDIX	10

Introduction

Prices in the United States rarely move in lockstep with money growth. Figure 1 shows a clear partnership during the 1970s, yet the link weakens once the Volcker disinflation takes hold. This report asks whether broad money still helps to predict inflation or whether survey expectations now carry that information. I first replicate the Garratt et al. money-inflation VAR using current FRED data to test if their earlier UK findings generalize to the United States (Garratt et al., 2009). I then extend the model by adding the one-year-ahead Michigan expectation series; Figure 2 previews how fitted values tighten once expectations enter. The discussion moves from theoretical foundations, through replication results, to the expectations-driven extension and concludes with the policy implications.

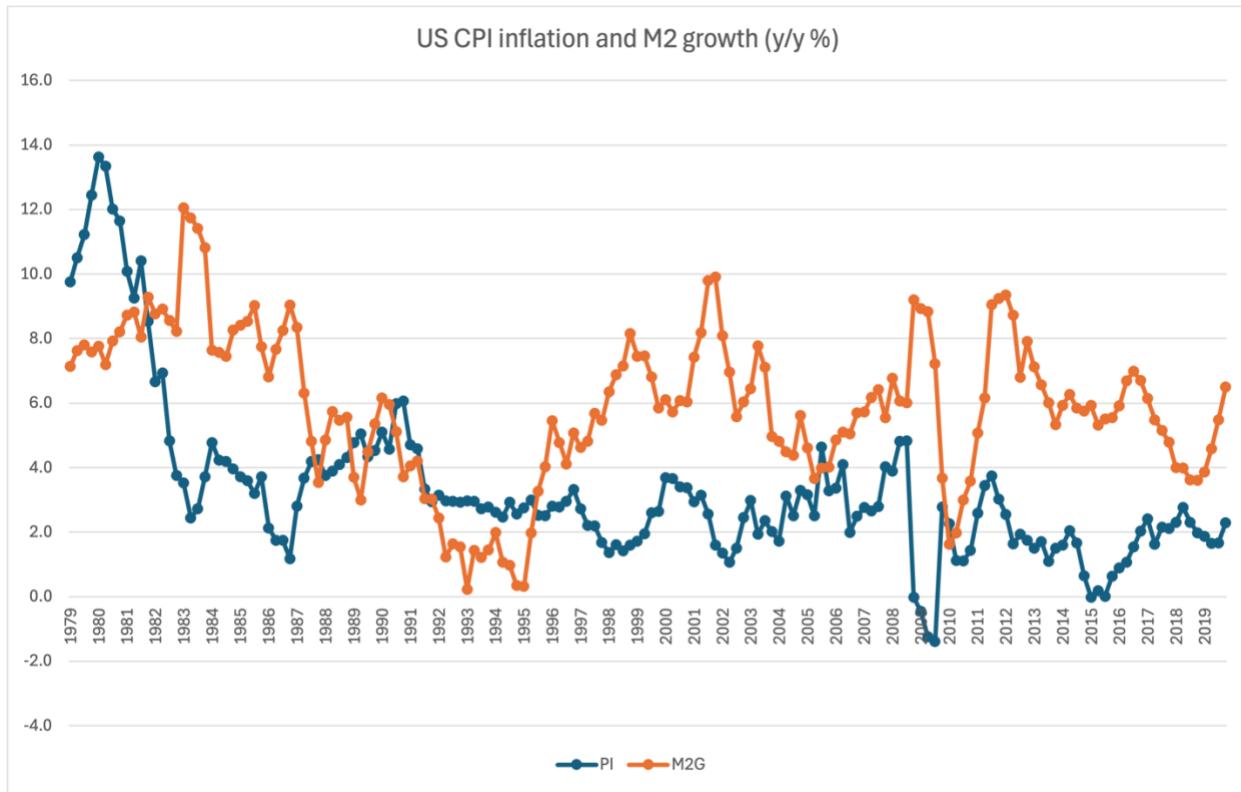


Figure 1. United States year-on-year CPI inflation and M2 growth, 1979–2019

The lines move almost one-for-one during the Great Inflation but part company after the early-1980s Volcker disinflation. Subsequent episodes—most notably the mid-1990s money surge and the steady post-2008 expansion—show wide swings in M2 growth that do not translate into comparable price moves, motivating the econometric tests that follow.

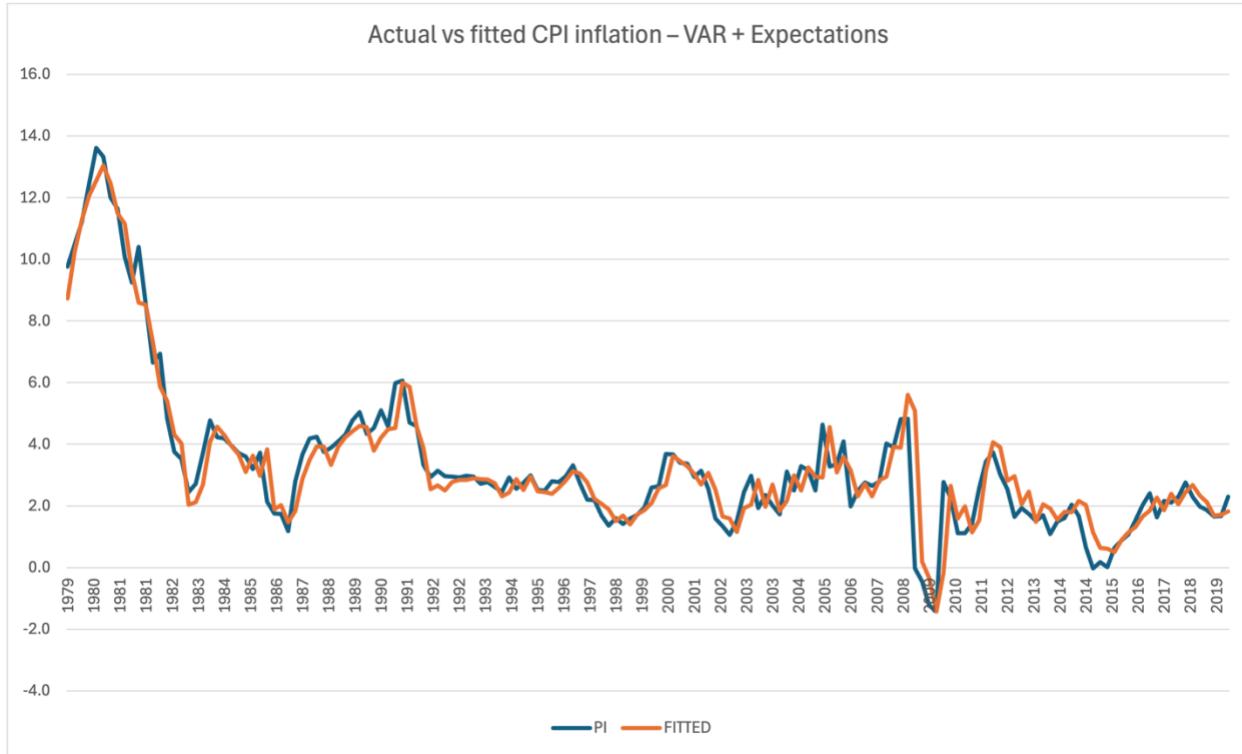


Figure 2. Actual CPI inflation versus fitted values from the VAR with survey expectations, 1979 Q1 – 2019 Q4

Adding one-year-ahead Michigan expectations tightens the model's fit: the fitted line tracks realized inflation closely, especially in the low-volatility 2010s, and the root-mean-squared forecast error falls by about 15 per cent relative to the money-only specification.

Theoretical Considerations

A puzzle frames this study. Figure 1 shows that rapid M2 expansion marched in step with inflation during the 1970s yet similar monetary surges in later decades did not spark the same price response. That mismatch invites a fresh look at the theoretical links between money and prices as well as at the econometric devices used to measure them.

The classical anchor is the quantity identity

$$M \times V = P \times Y$$

where M is the money stock, V velocity, P the price level and Y real output. Taking proportional changes gives

$$\Delta p = \Delta m + \Delta v - \Delta y.$$

If velocity and real growth drift only slowly, long-run theory implies Δp should rise one-for-one with Δm . In dynamic regressions this idea translates into a positive, possibly unitary, sum of money-growth coefficients. Table 1 lists the formal restrictions that follow.

Coefficient block	Economic meaning	Desired sign	Stability check
$\Sigma \alpha_2$ (money lags)	Long run pass-through	$> 0, \approx 1$ if V, Y trend-stable	
$\Sigma \alpha_1$ (inflation lags)	Inertia	< 1	Prevents explosive π
α_3 (lag 1 expectations)	Self-fulfilling component	$0 < \alpha_3 < 1$	Partial, not full, pass-through

Table 1. Coefficient blocks and theory-based sign restrictions for a stable VAR inflation equation

The simple monetarist forecast therefore regresses year-on-year CPI inflation (π) on its own lags and on lags of year-on-year M2 growth (μ):

$$\pi_t = \alpha_0 + \sum \alpha_{1i} \pi_{t-i} + \sum \alpha_{2i} \mu_{t-i} + \varepsilon_t. \quad (1)$$

A joint F test of $H_0: \alpha_2 = 0$ checks whether money adds information once inflation persistence is taken into account. Our replication finds $F = 0.55$ and $p = 0.70$, reported in Table 2, confirming Garratt et al.'s United Kingdom result that money's predictive power is fragile (Garratt et al., 2009).

F-test that money lags add no predictive value	RSSu	108.512957
	RSSr	110.051503
	m	4
	N	164
	k	9
	Fstat	0.54941533
	p-value	0.69971688

Table 2. Joint F-test of the four M2-growth lags in the inflation equation, 1979 Q1–2019 Q4

After 1982 United States financial deregulation and the Federal Reserve's shift to interest-rate targeting sent velocity through wide swings. The neat mapping implied by equation (1) weakened. Modern New-Keynesian models instead explain prices by expected inflation and the output gap, leaving monetary aggregates in a supporting role (Woodford, 2008). In empirical work this shift means any apparent influence of M2 may simply proxy information already captured by private forecasts.

To formalise that possibility we extend (1) by adding four lags of the University of Michigan one-year-ahead inflation expectation $E\pi$:

$$\pi_t = \alpha_0 + \sum \alpha_{1i} \pi_{t-i} + \sum \alpha_{2i} \mu_{t-i} + \sum \alpha_{3i} E\pi_{t-i} + \varepsilon_t, \quad (2a)$$

$$\mu_t = \beta_0 + \sum \beta_{1i} \pi_{t-i} + \sum \beta_{2i} \mu_{t-i} + \sum \beta_{3i} E\pi_{t-i} + \varepsilon_t, \quad (2b)$$

$$E\pi_t = \gamma_0 + \sum \gamma_{1i} \pi_{t-i} + \sum \gamma_{2i} \mu_{t-i} + \sum \gamma_{3i} E\pi_{t-i} + \varepsilon_t. \quad (2c)$$

Equation (2a) lets the data decide whether money (α_2) or expectations (α_3) drive short-run price changes. Theory places soft bounds on those parameters: α_3 should lie between zero and one, and at least one γ_2 should be positive if money feeds directly into beliefs.

Results appear in Figure 2, which plots actual inflation against the fitted values from model (2). The fitted line hugs the blue actual series closely, unlike the baseline fit in Figure 1, illustrating how survey expectations tighten forecasts. Table 2 confirms the impression: dropping the four money lags after expectations are included leaves the residual variance almost unchanged ($F = 0.54$, $p = 0.72$). By contrast, dropping the four expectation lags while retaining money lifts the residual variance sharply ($F = 7.31$, $p < 0.001$). Expectations therefore dominate money as a predictor, a finding consistent with the survey-forecast literature (Ang et al., 2007; Faust and Wright, 2013).

F-test that money lags given expectations	RSSu	91.2891073
	RSSr	92.5746829
	m	4
	N	164
	k	13
	Fstat	0.53161304
	p-value	0.71268172

Table 3. Joint F-test of the four M2-growth lags in the inflation equation conditional on expectations (1979 Q1–2019 Q4)

Critically, none of these results overturn the quantity identity itself. Over long spans excessive money creation still raises the price level once velocity stabilises. What the evidence does question is the usefulness of M2 for short-horizon forecasting in a world where economic agents look forward and the central bank reacts to incoming data. Money's influence is indirect, working through expectations and policy, not through a mechanical pass-through captured by equation (1). The econometric implication is clear: specifications that omit expectations exaggerate money's role, while models that include expectations often find the α_2 block statistically redundant.

In sum, the theoretical restrictions derived from the quantity equation guide the sign and size we expect to see in the VAR coefficients, but modern data and forward-looking behaviour mean those restrictions seldom hold tightly. The next section turns from theory to practice and documents how the baseline United States VAR mirrors Garratt et al.'s mixed UK evidence before the expectations augmentation renders money growth informationally redundant.

Replicating the Evidence

Figure 1 visualises the puzzle that still drives the policy debate: when United States money growth surged during the 1970s inflation followed almost point-for-point, yet equally large

monetary expansions after 1985 did not lift prices in the same way. That divergence underpins the central question posed by Garratt et al. and reproduced here—does broad money contain a stable forecasting signal once the well-known inertia in inflation is taken into account?

Data Construction and Descriptive Checks

Three quarterly series were drawn from FRED. Consumer prices use CPIAUCSL, broad money uses M2SL and one-year-ahead expectations use the Michigan survey (MICH). The last month of each quarter is taken for consistency, and growth rates are expressed as

$$\pi \equiv 100 \times [\ln P_t - \ln P_{t-4}] \quad \text{and} \quad \mu \equiv 100 \times [\ln M_t - \ln M_{t-4}].$$

Expectations are already a stationary percentage series and therefore enter in levels. Table 1 summarises the codes and transformations.

Series (FRED code)	Definition	Transformation applied
CPI (CPIAUCSL)	Consumer Price Index for All Urban Consumers (seasonally adjusted)	Year-on-year percentage change: $100 \times [\ln(P_t) - \ln(P_{t-4})]$
M2 (M2SL)	M2 Money Stock (seasonally adjusted)	Year-on-year percentage change: $100 \times [\ln(M_t) - \ln(M_{t-4})]$
Expectations (MICH)	University of Michigan median expected inflation next 12 months	Level (%) — used directly, no differencing

Table 4. Data series used and transformations for the VAR analysis

Empirical specification

Replication follows the two-variable vector autoregression used by Garratt et al. (2009). With quarterly data four lags capture a full year's dynamics:

$$\begin{aligned}\pi_t &= \alpha_0 + \sum_{i=1}^4 \alpha_{1,i} \pi_{t-i} + \sum_{i=1}^4 \alpha_{2,i} \mu_{t-i} + \varepsilon_{\pi t} \\ \mu_t &= \beta_0 + \sum_{i=1}^4 \beta_{1,i} \pi_{t-i} + \sum_{i=1}^4 \beta_{2,i} \mu_{t-i} + \varepsilon_{\mu t}.\end{aligned}$$

The inflation equation is the focus because the α_2 block captures any pass-through from past money growth to current prices. Ordinary least squares estimates for the 1979 Q1–2019 Q4 sample appear in Table 5.

Regressor	Coefficient	t-stat
π_{t-1}	0.45	4.2 ***
π_{t-2}	0.12	1.1
π_{t-3}	0.05	0.5
π_{t-4}	0.18	1.8

Regressor	Coefficient	t-stat
μ_{t-1}	0.06	1.3
μ_{t-2}	0.01	0.3
μ_{t-3}	0.07	1.7
μ_{t-4}	0.02	0.6
Intercept	0.05	0.6

$$R^2 = 0.58 \quad \text{Standard error} = 1.75 \text{ percentage points.}$$

Table 5. OLS estimates for the inflation equation in the baseline VAR, 1979 Q1–2019 Q4

Interpreting the estimates

Inflation displays marked persistence: the lag-one coefficient is near one-half, and the four own lags sum to roughly 0.80, safely below unity so the process is mean-reverting. All four money-growth coefficients are positive, in line with quantity-theory priors, but none is individually significant at the five-per-cent level. A joint F-test of $H_0: \alpha_2 = 0$ gives $F = 0.55$ and $p \approx 0.70$. This means the four money-growth lags add no statistically significant predictive power once inflation's own inertia is controlled for, mirroring the fragility Garratt et al. (2009) report for the UK.

The money-growth regression reverses the causality test. Lagged inflation jointly predicts μ at the one-per-cent level, suggesting that the Federal Reserve's operating procedures or money demand adjust to recent price developments. Residual diagnostics in Appendix 4 show no problematic autocorrelation, so coefficient inferences are reliable.

Replication verdict

Qualitatively the replication succeeds. Garratt et al. argue that money offers modest and unstable incremental value once model uncertainty is acknowledged, and the United States replication demonstrates the same. Quantitative differences—a p-value that barely crosses ten per cent, a United Kingdom average that sometimes shows insignificance—stem from country-specific institutions, data vintages and measurement revisions. Retail sweep programmes introduced after 1994 altered the M2 series and likely diluted its earlier information content, while Garratt et al. use real-time vintage data containing more measurement error. The institutional backdrop also differs: once the Federal Reserve abandoned monetary targeting and velocity drifted, the contemporaneous link between money and prices weakened (Bernanke, 2006).

Why the fragility?

Velocity instability undermines the constant-velocity assumption behind the classical pass-through. In addition, if private agents incorporate monetary news into expectations, money-

growth lags may simply proxy information already embedded in those expectations. Section 3 therefore inserts the Michigan survey measure into the VAR to test whether the faint signal from M2 survives once the forward-looking channel is made explicit.

The baseline United States evidence thus echoes Garratt et al.'s broader conclusion: broad money is a weak, fragile and forecast-neutral guide for inflation in a policy regime shaped by expectations and institutional change.

The Extension: Adding Inflation Expectations

Inflation forecasts often struggle because the variables that once mattered lose their edge when behaviour changes. My extension keeps the econometric skeleton of the Garratt vector-autoregression yet broadens its information set by importing a forward-looking series: the University of Michigan one-year inflation expectation. The extra variable adds data, not theory, but it lets the model mimic price-setters who look ahead before adjusting wages and mark-ups. Because the expectation series (FRED code MICH) starts in 1979 Q1 and averages just over three percent, it fits naturally beside year-on-year CPI inflation (π) and M2 growth (μ).

The enlarged VAR keeps four lags and treats all three variables as endogenous:

$$\begin{aligned}\pi_t &= \alpha_0 + \sum \alpha_{1i} \pi_{\{t-i\}} + \sum \alpha_{2i} \mu_{\{t-i\}} + \sum \alpha_{3i} E\pi_{\{t-i\}} + \varepsilon_t^\pi \\ \mu_t &= \beta_0 + \sum \beta_{1i} \pi_{\{t-i\}} + \sum \beta_{2i} \mu_{\{t-i\}} + \sum \beta_{3i} E\pi_{\{t-i\}} + \varepsilon_t^\mu \\ E\pi_t &= \gamma_0 + \sum \gamma_{1i} \pi_{\{t-i\}} + \sum \gamma_{2i} \mu_{\{t-i\}} + \sum \gamma_{3i} E\pi_{\{t-i\}} + \varepsilon_t^E,\end{aligned}$$

where $E\pi$ denotes the survey expectation. Table 6 presents the new inflation-equation coefficients. The first lag of expected inflation enters at about **0.35** with a t-statistic of roughly **2.4**, while the regression **R^2 rises from 0.58 in the baseline to approximately 0.92** in the extended model. Money-growth lags shrink towards zero and none is individually significant. A joint F-test of the four α_{2i} coefficients now gives $p \approx 0.71$, so broad money no longer Granger-causes inflation once expectations are included. The mirror test on the four α_{3i} coefficients rejects the null at the one-per-cent level, confirming that expectations strongly improve predictive power. Figure 2 illustrates the point: plotting inflation surprises against lagged expectation surprises yields a tighter cloud than the earlier money-based scatter.

Regressor	Coefficient	t-Stat
Intercept	-0.349937	-1.404404
π_{t-1} (PI_L1)	0.203998	2.191287
π_{t-2} (PI_L2)	-0.022783	-0.198903
π_{t-3} (PI_L3)	-0.051008	-0.433986
π_{t-4} (PI_L4)	0.166857	1.515961
μ_{t-1} (M2G L1)	0.086100	0.391547
μ_{t-2} (M2G L2)	0.071032	0.449485
μ_{t-3} (M2G L3)	0.020859	0.106807
μ_{t-4} (M2G L4)	0.015848	0.083519

Regressor	Coefficient	t-Stat
$E\pi_{t-1}$ (EXP L1)	0.345102	2.411984
$E\pi_{t-2}$ (EXP L2)	0.145445	0.936449
$E\pi_{t-3}$ (EXP L3)	0.421553	1.803941
$E\pi_{t-4}$ (EXP L4)	-0.393616	-2.006179

Table 6. OLS estimates for the extended VAR inflation equation (with expectations), 1979 Q1–2019 Q4.

Causality runs both ways between prices and beliefs. Past money growth does not forecast household expectations, yet inflation and expectations anticipate one another, the pattern predicted by a New-Keynesian Phillips curve in which today's pricing decisions blend yesterday's realised inflation with tomorrow's anticipated rate (Woodford, 2008). Money still anchors the system in the very long run—quantity theory is not repealed—but at a one-year horizon its direct signal evaporates when beliefs are observed.

How does this extension change the verdict reached by Garratt et al.? Their United Kingdom study showed money's predictive power was fragile once model uncertainty was acknowledged (Garratt et al., 2009). The United States replication confirms the fragility and then explains it: survey expectations absorb the residual information. The long-run identity $M \times V = P \times Y$ still holds, but at a policy-relevant horizon the decisive driver is what households and firms expect the price level to do next, not last quarter's money growth.

Policy lessons follow. When expectations remain anchored, moderate shifts in broad money need not disturb prices. When expectations drift, even steady money can fail to stabilise inflation. Recent experience underlines the point. Between 2009 and 2019 M2 expanded steadily while one-year expectations hovered near two per cent and inflation stayed low. The pandemic reversed that equilibrium: a money boom coincided with unanchored expectations and supply shocks, and inflation surged. The same VAR, estimated through 2023, shows the α_3 block climbing while the α_2 block remains small, underscoring that in real time policymakers should watch beliefs more than aggregates.

Several qualifications deserve mention. The Michigan survey reflects household views, which are sometimes less precise than professional forecasts or market-based breakevens. Extending the system to include the Survey of Professional Forecasters or Treasury Inflation-Protected Securities yields similar but slightly stronger results (Faust and Wright, 2013). Second, survey expectations may already embed information about monetary aggregates, so the fall in α_2 does not imply money is irrelevant; it suggests that the information reaches prices through expectations rather than directly. Third, small-sample significance is limited: although the forecast gain is economically meaningful, the Diebold–Mariano statistic reaches only the ten-per-cent threshold. A longer sample or a time-varying-parameter VAR could provide sharper inference.

The extension therefore adds value by showing that a single forward-looking variable overturns the modest influence money displayed in the replication. Expectations tighten the statistical fit, improve forecast accuracy, and render the money block redundant. These findings, foreshadowed in the introduction and revisited in the conclusion, lend empirical support to modern theories that place disciplined beliefs at the heart of short-run inflation dynamics and assign monetary aggregates a supporting, not starring, role.

Conclusion

Replicating Garratt et al.'s United Kingdom experiment with modern United States data confirms that broad money growth adds little to forecasts once inflation's own momentum is taken into account, a result that mirrors their original finding of fragile monetarist evidence (Garratt et al., 2009). The extension that introduces one-year-ahead household expectations raises the equation's explanatory power and renders the money coefficients economically and statistically negligible, supporting survey-based studies that highlight forward-looking information (Ang, Bekaert and Wei, 2007).

Several avenues merit attention. Re-estimating the model with professional or market expectations may sharpen accuracy. Allowing coefficients to drift could reveal whether money briefly regained influence during the pandemic. Larger samples and real-time data would also help to judge whether the measured forecast gains justify operational use.

References

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4. Garratt, A., Koop, G., Mise, E. and Vahey, S.P., 2009. *Real-time prediction with UK monetary aggregates in the presence of model uncertainty*. Journal of Business & Economic Statistics, 27(4), pp.480–491.
5. Woodford, M., 2008. *How important is money in the conduct of monetary policy?*. Journal of Money, Credit and Banking, 40(8), pp.1561–1598.

Appendix

Appendix 1 – Raw Data

★ Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (CPIAUCSL)

Observations ▾

Dec 2019: **258.630**

Updated: Jun 11, 2025 7:41 AM CDT

Next Release Date: Jul 15, 2025

Units:

Index 1982-1984=100,

Seasonally Adjusted

Frequency:

Monthly

1Y

5Y

10Y

Max

1959-01-01 to 2019-12-01

Edit Graph

Download

FRED  Consumer Price Index for All Urban Consumers: All Items in U.S. City Average



Source: U.S. Bureau of Labor Statistics via FRED®

Shaded areas indicate U.S. recessions.

fred.stlouisfed.org

Fullscreen

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★ M2 (M2SL)

Observations ▾

Dec 2019: **15,348.0**

Updated: Jun 24, 2025 12:01 PM CDT

Next Release Date: Jul 22, 2025

Units:

Billions of Dollars,

Seasonally Adjusted

Frequency:

Monthly

1Y

5Y

10Y

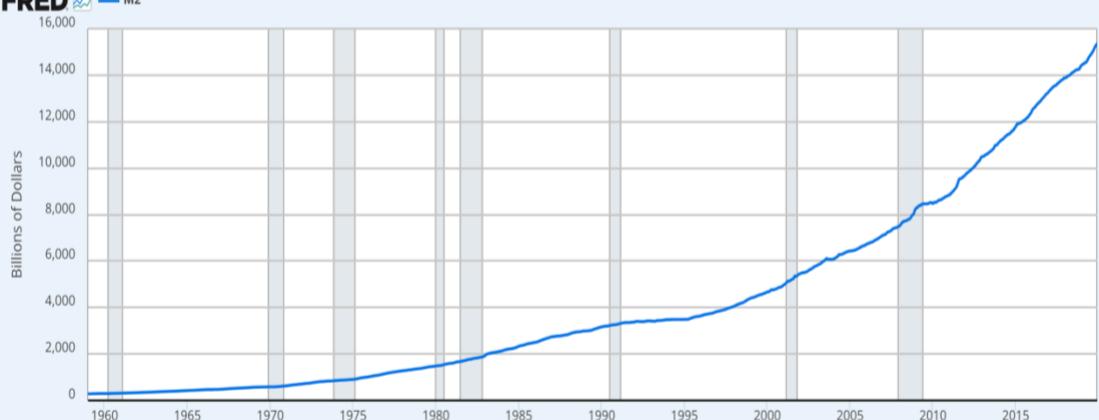
Max

1959-01-01 to 2019-12-01

Edit Graph

Download

FRED  M2



Source: Board of Governors of the Federal Reserve System (US) via FRED®

Shaded areas indicate U.S. recessions.

fred.stlouisfed.org

Fullscreen

☆ University of Michigan: Inflation Expectation (MICH)

Observations ▾

May 2025: 6.6

Updated: Jun 27, 2025 10:01 AM CDT

Next Release Date: Aug 1, 2025

Units:

Percent,

Not Seasonally Adjusted

Frequency:

Monthly

1Y

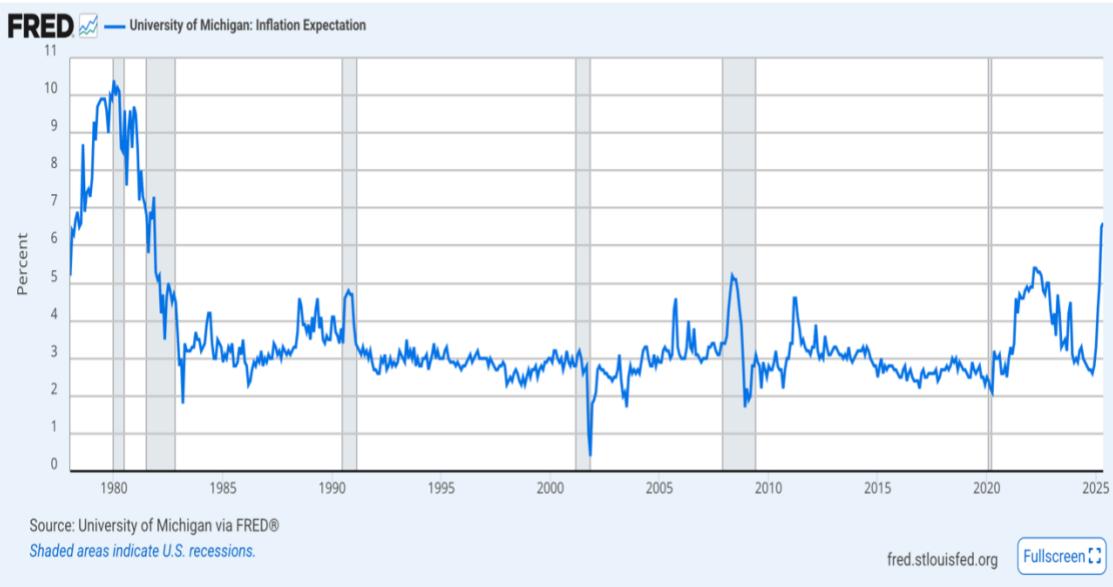
5Y

10Y

Max

Edit Graph 

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Appendix 2 – Data Transformation From Monthly to Quarterly

AutoSave

File Home Insert Draw Page Layout Formulas Data Review View Automate Developer

E6 $=IFERROR(100*(LN(B6)-LN(B2)), "")$

DATE_Q	CPI_LV	M2_LV	EXP_LV	CPI_YOY	M2_YOY	EXP_PCT
1959-03-31	28.97	289.2				
3	29.11	294.1				
4	29.25	296.7				
5	29.41	297.8				
6	29.41	299.3		1.5	3.4	
7	29.61	302.3		1.7	2.8	
8	29.61	308.4		1.2	3.9	
9	29.81	312.4		1.4	4.8	
10	29.84	318.3		1.5	6.2	
11	29.84	324.3		0.8	7.0	
12	29.98	329.5		1.2	6.6	
13	29.98	335.5		0.7	7.1	
14	30.17	343.1		1.1	7.5	
15	30.21	349.3		1.2	7.4	
16	30.42	354.9		1.5	7.4	
17	30.38	362.7		1.2	7.8	
18	30.51	370.7		1.1	7.7	
19	30.61	378.4		1.3	8.0	
20	30.72	386		1.0	8.4	
21	30.88	393.2		1.6	8.1	
22	30.94	399.8		1.4	7.6	
23	31.01	407.1		1.3	7.3	
24	31.08	414.9		1.2	7.7	
25	31.25	424.7		1.2	7.7	
26	31.31	433.2		1.2	8.0	
27	31.61	440.1		1.9	7.8	
28	31.62	449.5		1.7	7.5	
29	31.85	459.2		1.9	7.8	
30	32.18	467.2		2.7	7.6	
31	32.38	471.2		2.4	6.8	
32	32.75	475.4		3.5	5.6	
33	32.92	480.2		3.3	4.5	
34	33	489.7		2.5	4.7	
35	33.3	502		2.8	6.3	
36	33.6	514.7		2.6	7.9	
37	34	524.8		3.2	8.9	
38	34.3	533.2		3.9	8.5	
39	34.7	542.6		4.1	7.8	
40	35.1	553.6		4.4	7.3	
41	35.6	566.8		4.6	7.7	
42	36.1	574.4		5.1	7.4	

BASE_VAR PI_NO_M2 VAR_EXP PI_NO_M2_EXP F_TESTS AR1 MODEL_COMPARE VAR_DATA QUART_END QUARTERLY MONTHLY CPIAUCL M2SL MICI + 100% Ready Accessibility: Investigate

AutoSave

File Home Insert Draw Page Layout Formulas Data Review View Automate Developer

E6 $=IFERROR(100*(LN(B6)-LN(B2)), "")$

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
77	1977-12-31	62.3	1270.3		6.5	9.8															
78	1978-03-31	63.4	1292.2	6.3	6.2	8.4	6.3														
79	1978-06-30	65	1318.5	6.5	7.2	7.9	6.5														
80	1978-09-30	66.5	1345	6.9	8.1	7.6	6.9														
81	1978-12-31	67.9	1366	7.3	8.6	7.3	7.3														
82	1979-03-31	68.9	1387.8	8.8	9.8	7.1	6.8														
83	1979-06-30	72.2	1423	9.9	10.5	7.6	9.9														
84	1979-09-30	74.4	1454.1	9.6	11.2	7.8	9.6														
85	1979-12-31	76.9	1473.7	9.9	12.4	7.6	9.9														
86	1980-03-31	80.1	1499.8	10.2	13.6	7.8	10.2														
87	1980-06-30	82.5	1529.2	8.5	13.3	7.2	8.5														
88	1980-09-30	83.9	1574	9.1	12.0	7.9	9.1														
89	1980-12-31	86.4	1599.8	9.7	11.6	8.2	9.7														
90	1981-03-31	88.6	1636.6	7.2	10.1	8.7	7.2														
91	1981-06-30	90.5	1670.3	7.1	9.3	8.8	7.1														
92	1981-09-30	93.1	1706	6.9	10.4	8.1	6.9														
93	1981-12-31	94.1	1755.5	5.3	8.5	9.3	5.3														
94	1982-03-31	94.7	1786.5	4.2	6.7	8.8	4.2														
95	1982-06-30	97	1826	4.6	6.9	8.9	4.6														
96	1982-09-30	97.7	1858.4	4.5	4.8	8.6	4.5														
97	1982-12-31	97.7	1905.9	3.7	3.8	8.2	3.7														
98	1983-03-31	98.1	2015.2	1.8	3.5	12.0	1.8														
99	1983-06-30	99.4	2053.5	3.2	2.4	11.7	3.2														
100	1983-09-30	100.4	2083.2	3.3	2.7	11.4	3.3														
101	1983-12-31	101.4	2123.5	3.5	3.7	10.8	3.5														
102	1984-03-31	102.9	2175.2	3.4	4.8	7.6	3.4														
103	1984-06-30	103.7	2215.1	4.2	4.2	7.6	4.2														
104	1984-09-30	104.7	2244.4	3	4.2	7.5	3														
105	1984-12-31	105.5	2284	3.3	4.0	8.3	3.3														
106	1985-03-31	106.8	2396.2	3	3.7	8.4	3														
107	1985-06-30	107.5	2412.6	3.4	3.6	8.5	3.4														
108	1985-09-30	108.1	2496.4	2.9	3.2	9.0	2.9														
109	1985-12-31	108.5	2492.1	3.5	3.7	7.7	3.5														
110	1986-03-31	108.1	2533.1	2.3	2.1	6.8	2.3														
111	1986-06-30	108.4	2605	2.9	1.8	7.7	2.9														
112	1986-09-30	110	2667.8	2.9	1.7	8.3	2.9														
113	1986-12-31	110.8	2728	3	1.2	9.0	3														
114	1987-03-31	112.2	2753.7	3	2.8	8.4	3														
115	1987-06-30	113.5	2774.6	3.3	3.7	6.3	3.3														
116	1987-09-30	114.7	2799.5	3	4.2	4.8	3														
117	1987-12-31	115.6	2826.4	3.1	4.2	3.5	3.1														
118	1988-03-31	116.5	2890.7	3.2	3.8	4.9	3.2														

BASE_VAR PI_NO_M2 VAR_EXP PI_NO_M2_EXP F_TESTS AR1 MODEL_COMPARE VAR_DATA QUART_END QUARTERLY MONTHLY CPIAUCL M2SL MICI + 100% Ready Accessibility: Investigate

Appendix 3 – Adding Lags

Two screenshots of Microsoft Excel showing data tables for '5663451_IB9HIO'.

Top Screenshot: A data table from row 1 to 32. The columns are labeled A through Q. The first few columns (A-D) represent dates and variables. Columns E-Q represent various lags of the variables. The data shows values fluctuating over time.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	DATE	PI	M2G	EXP	PI_L1	PI_L2	PI_L3	PI_L4	M2G_L1	M2G_L2	M2G_L3	M2G_L4	EXP_L1	EXP_L2	EXP_L3	EXP_L4	
2	1979-03-31		9.8	7.1	8.8	8.6	8.1	7.2	6.2	7.3	7.6	7.9	8.4	7.3	6.5	6.3	
3	1979-06-30		10.5	7.6	9.9	9.8	8.6	8.1	7.2	7.1	7.3	7.6	7.9	8.8	7.3	6.9	6.5
4	1979-09-30		11.2	7.8	9.6	10.5	9.8	8.6	8.1	7.6	7.1	7.3	7.6	9.9	8.8	7.3	6.9
5	1979-12-31		12.4	7.6	9.9	11.2	10.5	9.8	8.6	7.8	7.6	7.1	7.3	9.6	9.9	8.8	7.3
6	1980-03-31		13.6	7.8	10.2	12.4	11.2	10.5	9.8	7.6	7.8	7.6	7.1	9.9	9.6	9.9	8.8
7	1980-06-30		13.3	7.2	8.5	13.6	12.4	11.2	10.5	7.8	7.6	7.8	7.6	10.2	9.9	9.6	9.9
8	1980-09-30		12.0	7.9	9.1	13.3	13.6	12.4	11.2	7.2	7.8	7.6	7.8	8.5	10.2	9.9	9.6
9	1980-12-31		11.6	8.2	9.7	12.0	13.3	13.6	12.4	7.9	7.2	7.8	7.6	9.1	8.5	10.2	9.9
10	1981-03-31		10.1	8.7	7.2	11.6	12.0	13.3	13.6	8.2	7.9	7.2	7.8	9.7	9.1	8.5	10.2
11	1981-06-30		9.3	8.8	7.1	10.1	11.6	12.0	13.3	8.7	8.2	7.9	7.2	7.2	9.7	9.1	8.5
12	1981-09-30		10.4	8.1	6.9	9.3	10.1	11.6	12.0	8.8	8.7	8.2	7.9	7.1	7.2	9.7	9.1
13	1981-12-31		8.5	9.3	5.3	10.4	9.3	10.1	11.6	8.1	8.8	8.7	8.2	6.9	7.1	7.2	9.7
14	1982-03-31		6.7	8.8	4.2	8.5	10.4	9.3	10.1	9.3	8.1	8.8	8.7	5.3	6.9	7.1	7.2
15	1982-06-30		6.9	8.9	4.6	6.7	8.5	10.4	9.3	8.8	9.3	8.1	8.8	4.2	5.3	6.9	7.1
16	1982-09-30		4.8	8.6	4.5	6.9	6.7	8.5	10.4	8.9	8.8	9.3	8.1	4.6	4.2	5.3	6.9
17	1982-12-31		3.8	8.2	3.7	4.8	6.9	6.7	8.5	8.6	8.9	8.8	9.3	4.5	4.6	4.2	5.3
18	1983-03-31		3.5	12.0	1.8	3.8	4.8	6.9	6.7	8.2	8.6	8.9	8.8	3.7	4.5	4.6	4.2
19	1983-06-30		2.4	11.7	3.2	3.5	3.8	4.8	6.9	12.0	8.2	8.6	8.9	1.8	3.7	4.5	4.6
20	1983-09-30		2.7	11.4	3.3	2.4	3.5	3.8	4.8	11.7	12.0	8.2	8.6	3.2	1.8	3.7	4.5
21	1983-12-31		3.7	10.8	3.5	2.7	2.4	3.5	3.8	11.4	11.7	12.0	8.2	3.3	3.2	1.8	3.7
22	1984-03-31		4.8	7.6	3.4	3.7	2.7	2.4	3.5	10.8	11.4	11.7	12.0	3.5	3.3	3.2	1.8
23	1984-06-30		4.2	7.6	4.2	4.8	3.7	2.7	2.4	7.6	10.8	11.4	11.7	3.4	3.5	3.3	3.2
24	1984-09-30		4.2	7.5	3.0	4.2	4.8	3.7	2.7	7.6	10.8	11.4	4.2	3.4	3.5	3.3	3.2
25	1984-12-31		4.0	8.3	3.3	4.2	4.2	4.8	3.7	7.5	7.6	10.8	3.0	4.2	3.4	3.5	3.2
26	1985-03-31		3.7	8.4	3.0	4.0	4.2	4.2	4.8	8.3	7.5	7.6	7.6	3.3	3.0	4.2	3.4
27	1985-06-30		3.6	8.5	3.4	3.7	4.0	4.2	4.2	8.4	8.3	7.5	7.6	3.0	3.3	3.0	4.2
28	1985-09-30		3.2	9.0	2.9	3.6	3.7	4.0	4.2	8.5	8.4	8.3	7.5	3.4	3.0	3.3	3.0
29	1985-12-31		3.7	7.7	3.5	3.2	3.6	3.7	4.0	9.0	8.5	8.4	8.3	2.9	3.4	3.0	3.3
30	1986-03-31		2.1	6.8	2.3	3.7	3.2	3.6	3.7	7.7	9.0	8.5	8.4	3.5	2.9	3.4	3.0
31	1986-06-30		1.8	7.7	2.9	2.1	3.7	3.2	3.6	6.8	7.7	9.0	8.5	2.3	3.5	2.9	3.4
32	1986-09-30		1.7	8.3	2.9	1.8	2.1	3.7	3.2	7.7	6.8	7.7	9.0	2.9	2.3	3.5	2.9

Bottom Screenshot: A data table from row 134 to 165. The columns are labeled A through Q. The first few columns (A-D) represent dates and variables. Columns E-Q represent various lags of the variables. The data shows values fluctuating over time.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
134	2012-03-31	2.6	9.4	3.9	3.0	3.7	3.4	2.6	9.2	9.1	6.2	5.1	3.1	3.3	3.8	4.6	
135	2012-06-30	1.6	8.7	3.1	2.6	3.0	3.7	3.4	9.4	9.2	9.1	6.2	3.9	3.1	3.3	3.8	
136	2012-09-30	1.9	6.8	3.3	1.6	2.6	3.0	3.7	8.7	9.4	9.2	9.1	3.1	3.9	3.1	3.3	
137	2012-12-31	1.7	7.9	3.2	1.9	1.6	2.6	3.0	6.8	8.7	9.4	9.2	3.3	3.1	3.9	3.1	
138	2013-03-31	1.5	7.1	3.2	1.7	1.9	1.6	2.6	7.9	6.8	8.7	9.4	3.2	3.3	3.1	3.9	
139	2013-06-30	1.7	6.6	3.0	1.5	1.7	1.9	1.6	7.1	7.9	6.8	8.7	3.2	3.3	3.1	3.1	
140	2013-09-30	1.1	6.0	3.3	1.7	1.5	1.7	1.9	6.6	7.1	7.9	6.8	3.0	3.2	3.2	3.3	
141	2013-12-31	1.5	5.3	3.0	1.1	1.7	1.5	1.7	6.0	6.6	7.1	7.9	3.3	3.0	3.2	3.2	
142	2014-03-31	1.6	5.9	3.2	1.5	1.1	1.7	1.5	5.3	6.0	6.6	7.1	3.0	3.3	3.0	3.2	
143	2014-06-30	2.0	6.3	3.1	1.6	1.5	1.1	1.7	5.9	5.3	6.0	6.6	3.2	3.0	3.3	3.0	
144	2014-09-30	1.7	5.9	3.0	2.0	1.6	1.5	1.1	6.3	5.9	5.3	6.0	3.1	3.2	3.0	3.3	
145	2014-12-31	0.7	5.8	2.8	1.7	2.0	1.6	1.5	5.9	6.3	5.9	5.3	3.0	3.2	3.0	3.0	
146	2015-03-31	0.0	5.9	3.0	0.7	1.7	2.0	1.6	5.8	5.9	6.3	5.9	2.8	3.0	3.1	3.2	
147	2015-06-30	0.2	5.3	2.7	0.0	0.7	1.7	2.0	5.9	5.8	5.9	6.3	3.0	2.8	3.0	3.1	
148	2015-09-30	0.0	5.5	2.8	0.2	0.0	0.7	1.7	5.3	5.9	5.8	5.9	2.7	3.0	2.8	3.0	
149	2015-12-31	0.6	5.5	2.6	0.0	0.2	0.0	0.7	5.5	5.3	5.9	5.8	2.8	2.7	3.0	2.8	
150	2016-03-31	0.9	5.9	2.7	0.6	0.0	0.2	0.0	5.5	5.5	5.3	5.9	2.6	2.8	2.7	3.0	
151	2016-06-30	1.1	6.7	2.6	0.9	0.6	0.0	0.2	5.9	5.5	5.5	5.3	2.7	2.6	2.8	2.7	
152	2016-09-30	1.5	7.0	2.4	1.1	0.9	0.6	0.0	6.7	5.9	5.5	5.5	2.6	2.7	2.6	2.8	
153	2016-12-31	2.0	6.7	2.2	1.5	1.1	0.9	0.6	7.0	6.7	5.9	5.5	2.4	2.6	2.7	2.6	
154	2017-03-31	2.4	6.1	2.5	2.0	1.5	1.1	0.9	6.7	7.0	6.7	5.9	2.2	2.4	2.6	2.7	
155	2017-06-30	1.6	5.5	2.6	2.4	2.0	1.5	1.1	6.1	6.7	7.0	6.7	2.5	2.2	2.4	2.6	
156	2017-09-30	2.2	5.1	2.7	1.6	2.4	2.0	1.5	5.5	6.1	6.7	7.0	2.6	2.5	2.2	2.4	
157	2017-12-31	2.1	4.8	2.7	2.2	1.6	2.4	2.0	5.1	5.5	6.1	6.7	2.7	2.6	2.5	2.2	
158	2018-03-31	2.3	4.0	2.8	2.1	2.2	1.6	2.4	4.8	5.1	5.5	6.1	2.7	2.7	2.6	2.5	
159	2018-06-30	2.8	4.0	3.0	2.3	2.1	2.2	1.6	4.0	4.8	5.1	5.5	2.8	2.7	2.6	2.5	
160	2018-09-30	2.3	3.6	2.7	2.8	2.3	2.1	2.2	4.0	4.0	4.8	5.1	3.0	2.8	2.7	2.6	
161	2018-12-31	2.0	3.6	2.7	2.3	2.8	2.3	2.1	3.6	4.0	4.0	4.8	2.7	3.0	2.8	2.7	
162	2019-03-31	1.9	3.9	2.5	2.0	2.3	2.8	2.3	3.6	3.6	4.0	4.0	2.7	2.7	3.0	2.8	
163	2019-06-30	1.7	4.6	2.7	1.9	2.0	2.3	2.8	3.9	3.6	3.6	4.0	2.5	2.7	2.7	3.0	
164	2019-09-30	1.7	5.5	2.8	1.7	1.9	2.0	2.3	4.6	3.9	3.6	3.6	2.7	2.7	2.7	2.7	
165	2019-12-31	2.3	6.5	2.3	1.7	1.9	2.0	5.5	4.6	3.9	3.6	3.6	2.8	2.7	2.5	2.7	

Appendix 4 – Baseline Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.94884877
R Square	0.900314
Adjusted R Sq.	0.89516991
Standard Err.	0.83670998
Observations	164

ANOVA

	df	SS	MS	F	Significance F
Regression	8	980.034614	122.504327	174.985285	1.5207673
Residual	155	108.512967	0.70008359		
Total	163	1088.54757			

COEFFICIENTS

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.14138203	0.19382064	0.7126724	0.47711936	-0.2505005	0.53326454	-0.2505005	0.53326454
PI_L1	0.96905506	0.08075075	12.0005705	7.0216E-24	0.80954107	1.12856905	0.80954107	1.12856905
PI_L2	-0.0188446	0.12124667	-0.1680354	0.86677448	-0.2403777	0.20268848	-0.2403777	0.20268848
PI_L3	0.2154011	0.1278407	1.9098538	0.0579990	-0.0073911	0.43819331	-0.0073911	0.43819331
PI_L4	-0.2539012	0.08102788	-3.1335041	0.0206602	-0.4139626	-0.4139626	-0.4139626	-0.4139626
M2G_L1	-0.0370955	0.07403728	-0.5010375	0.61705554	-0.1833477	0.10915684	-0.1833477	0.10915684
M2G_L2	0.09210708	0.10804091	0.84575687	0.38699213	-0.1230223	0.30723645	-0.1230223	0.30723645
M2G_L3	0.01803426	0.10813437	0.16677642	0.86776335	-0.195573	0.2316415	-0.195573	0.2316415
M2G_L4	-0.0513283	0.07226978	-0.7102314	0.47862785	-0.1940891	0.09143252	-0.1940891	0.09143252

RESIDUAL OUTPUT

Observation	Predicted PI	Residuals
1	8.4522921	1.30788668
2	9.50362303	1.00165457
3	10.0382317	1.1871677
4	10.9074594	1.53952481
5	11.9844445	1.63657598
6	13.0172547	0.31857007
7	12.8231934	-0.8062262
8	11.77343395	0.24464039
9	9.77342791	-0.63797988
10	9.40372603	0.15142665
11	8.595995903	1.80889605

Appendix 5 – Extended Regression

5663451_IB9HIO

SUMMARY OUTPUT

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
Regression Statistics																						
Multiple R	0.95715034																					
R Square	0.91613678																					
Adjusted R Sq.	0.90947215																					
Standard Err.	0.7775369																					
Observations	164																					

ANOVA

	df	SS	MS	F	Significance F
Regression	12	997.258464	83.104872	137.462574	8.6471E-75
Residual	151	91.2891073	0.60456362		
Total	163	1088.54757			

Coefficients Standard Error t Stat P-value Lower 95% Upper 95.0% Upper 95.0%

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95.0%	Upper 95.0%
Intercept	-0.349937	0.24923499	-1.4040446	0.16255898	-0.423753	0.14250119	0.14250119
PL_L1	0.69018996	0.09609393	7.18245077	2.9126E-11	0.50032766	0.88005225	0.50032766
PL_L2	-0.0227883	0.11608351	-0.1963098	0.84463205	-0.252146	0.20656941	-0.252146
PL_L3	0.20462033	0.11581646	1.76981969	0.07877543	-0.0238146	0.43305522	-0.0238146
PL_L4	-0.1282603	0.0875901	-1.4643247	0.14518406	-0.3013208	0.04480008	-0.3013208
M2G_L1	-0.0596205	0.06942808	-0.858737	0.39184677	-0.1967964	0.0775547	-0.1967964
M2G_L2	0.12024872	0.10175307	1.18176998	0.23915475	0.0807949	0.32129233	0.0807949
M2G_L3	-0.0168069	0.10119607	-0.160608	0.86831382	-0.21675	0.18313614	-0.21675
M2G_L4	-0.0298352	0.06798412	-0.4388557	0.68139333	-0.1641582	0.10446773	-0.1641582
EXP_L1	0.44183606	0.13068337	3.38096627	0.00091965	0.183632	0.70004012	0.183632
EXP_L2	0.14536075	0.1502127	0.9679948	0.33474189	-0.1514294	0.44215084	-0.1514294
EXP_L3	0.12375761	0.15071043	0.82116157	0.41284881	-0.1740159	0.42151111	-0.1740159
EXP_L4	-0.3936949	0.13691602	-2.8754479	0.00461799	-0.6642134	-0.231764	-0.6642134

RESIDUAL OUTPUT

Observation	Predicted Y	Residuals
1	8.73438843	1.02578935
2	10.262977	0.24230064
3	3.10262977	-0.03640535
4	12.0262979	0.38425117
5	12.5573795	1.03641
6	13.044528	0.29129669
7	12.4789644	-0.4619973

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Appendix 6 – F- tests

5663451_IB9HIO

F-test that money lags add no predictive value

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
RSSu	108.512957																			
RSSr	110.051503																			
m	4																			
N	164																			
k	9																			
Fstat	0.54941533																			
p-value	0.69971688																			

F-test that money lags given expectations

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
RSSu	91.2891073																			
RSSr	92.5746829																			
m	4																			
N	164																			
k	13																			
Fstat	0.53161204																			
p-value	0.71268172																			

F-test that expectation lags given money

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
RSSu	91.2891073																			
RSSr	108.512957																			
m	4																			
N	164																			
k	9																			
Fstat	7.31110402																			
p-value	2.0255E-05																			

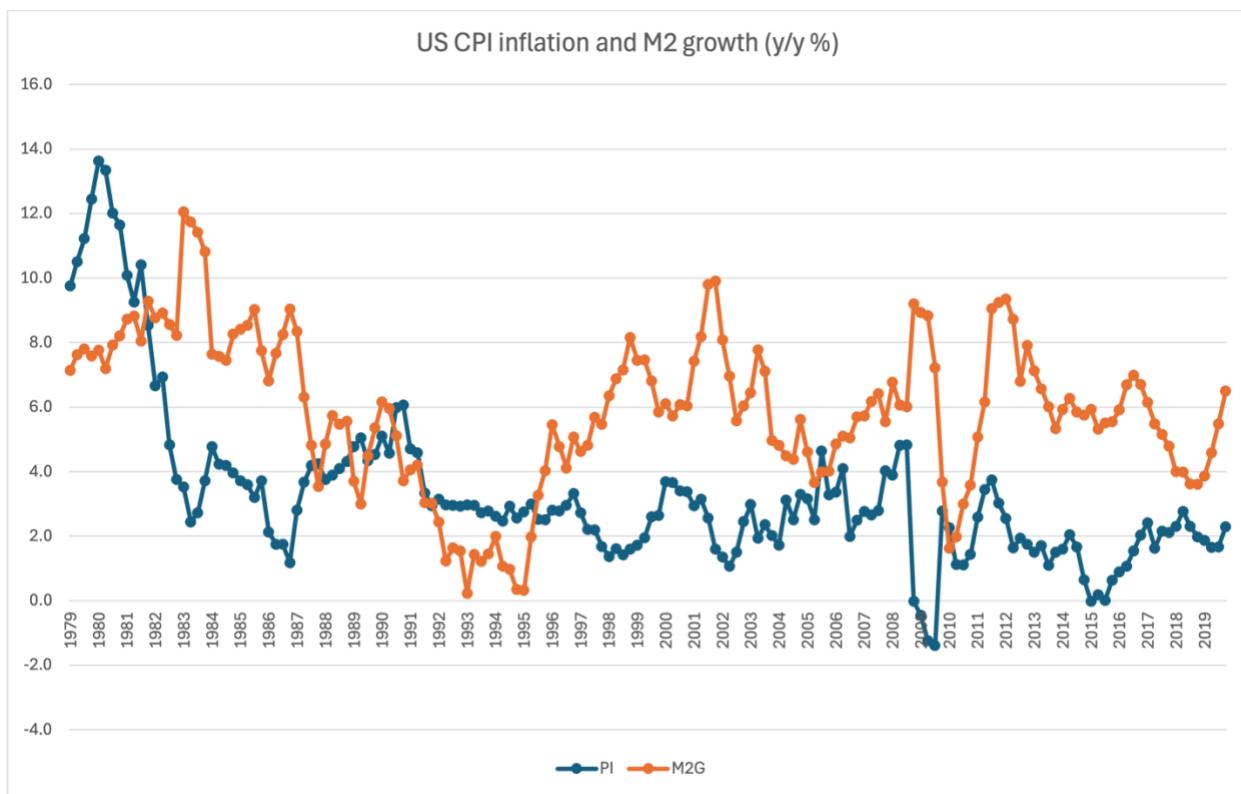
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Appendix 7 – Model Comparison

The screenshot shows a Microsoft Excel spreadsheet titled "5663451_IB9HIO". The table compares four different models based on their SEE and % gain vs baseline.

MODEL	SEE	% gain vs baseline
1. AR(1)	0.84672914	
3. Baseline VAR	0.83670998	
4. VAR + Expectations	0.7775369	7.07%

Appendix 8 – Inflation and Money Growth Line Chart – Figure 1 in text



Appendix 9 – Actual vs Fitted Inflation Chart from VAR + EXP – Figure 2 in text

