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Macro News in Market Moves: Classifying News through Asset Co-movements

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Abstract

This paper introduces CLONE (Classification Of News), a method that decomposes asset price movements into four types of macroeconomic news—aggregate demand, productivity, inflation, and monetary policy—based on joint changes in prices of stocks, bonds, and inflation swaps. CLONE's simplicity and forward-looking focus enable the identification of real-time economic signals that are critical for understanding market behavior and guiding policy decisions. We show that from 2004 to 2024 aggregate demand news historically dominated daily variation in asset prices, while inflation and monetary policy news have gained importance since 2021. We validate our method against sign-restricted VAR models and apply it to major U.S. macroeconomic data releases, providing insights into how market participants interpret and react to forward-looking information. We discuss several benefits of our approach relative to the standard sign restriction method.

Topics: Asset pricing, Macroeconomic news, Stock-bond correlation, Monetary policy, Inflation expectations

JEL codes: E44, G12, G14, E32

I. Introduction

Financial markets serve a crucial role in modern economies: they aggregate dispersed information held by households, businesses, and professional investors. Because the payoffs of financial assets are highly sensitive to future economic conditions, asset prices embed the collective beliefs about future economic growth, inflation, and monetary policy. Prices in sufficiently liquid markets also provide timely information, as they adjust almost instantly upon the arrival of news. It should therefore come as no surprise that central bankers rely on financial markets to infer timely signals about the macroeconomy (Bernanke, 2004; Poloz, 2018). Yet, isolating these signals is not easy. The sheer variety of asset classes, combined with the challenge of interpreting their joint movements, makes extracting relevant macroeconomic signals difficult.

To isolate these signals, traditional approaches, such as sign-restricted structural vector autoregressions (SVAR), typically map innovations in asset price movements to structural shocks within a dynamic modeling framework. The structure these frameworks provide has proven to be valuable, but it comes with the trade-off of requiring specific modeling assumptions and sophisticated estimation methods.[1] As a result, one may wonder whether these approaches are more complex than necessary to answer the question: what macroeconomic information can be inferred from asset prices on any given day?

We offer a model-free approach to answer this question. The approach is called CLONE-**Cl**assification **O**f **Ne**ws. At its core, CLONE classifies each day based on the realized combination of daily price changes of U.S. stocks, bonds, and inflation swaps.[2] These daily asset price changes capture forward-looking responses to "news" because asset prices reflect expectations (and uncertainties) about future payoffs sensitive to economic outcomes, and new information, or "news", leads to revisions in those expectations. We interpret each realized combination of asset price changes as reflecting the dominant news affecting markets on that day. Under our framework, each day reflects either (1) news of future aggregate demand, (2) news of future inflation, (3) news of future productivity, or (4) news of future monetary policy.

Our classification relies on U.S. stocks, bonds, and inflation swaps because of their clear link

[1]See (Cieslak and Pang, 2021; Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019) for recent applications of sign-restricted SVARs in financial market settings, and Fry and Pagan (2011) for a critical review on sign-restricted SVAR approaches in general.

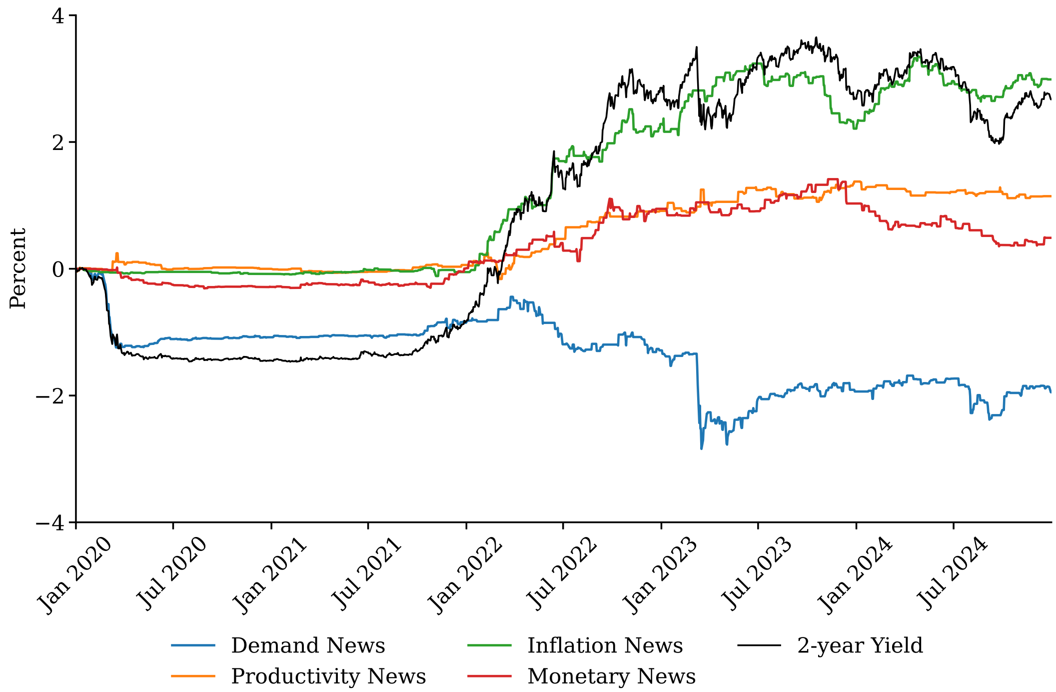
[2]Inflation swaps are a derivative contract in which two parties exchange cashflows based on realized inflation and the agreed-upon fixed swap rate. The fixed swap rate is a measure of inflation compensation: the expected inflation plus a risk premium to compensate for the uncertainty in the actual inflation rate to be realized over the contract's horizon.

to GDP growth, inflation expectations, and the path of expected interest rates. GDP growth expectations are embedded in stock prices because stocks are levered claims on firms' future profits, which are sensitive to GDP growth. Inflation expectations are captured by inflation swap rates, while the future path of expected interest rates can be inferred from government bond yields. When all three markets move in the same direction, we interpret this co-movement as news about future aggregate demand. Such news can reflect shifts in firms' future investment prospects or changes in expected consumption. By contrast, opposite changes in stocks and inflation swaps reveal either inflationary or productivity news, with the direction of bond yields distinguishing between the two. Inflationary news captures supply-side developments, such as expectations about firms' input costs that are perceived to feed through to aggregate inflation, whereas productivity news reflects changes in the economy's future productive capacity. Finally, monetary policy news is identified when bond yields move in the opposite direction of both stock prices and inflation swaps, reflecting, for example, changes in investors' perceptions of the Fed's policy stance.

To demonstrate the usefulness of our approach, consider the competing narratives that emerged during the inflationary surge from mid-2021 through 2023. One narrative emphasized overheating demand ignited by pandemic-era fiscal spending (Blanchard, 2021; Summers, 2021). A competing narrative focused on cost-push inflation pressures arising from supply chain disruptions and energy shocks (Guerrieri et al., 2022; Bernanke and Blanchard, 2023). Figure 1 lends support to the supply-driven interpretation. Notably, it does so without assuming demand- and supply-side channels are uncorrelated, albeit at the cost of not relying on a microfounded structural model (e.g., DSGE framework). The figure shows the cumulative change in the 2-year U.S. Treasury yield from 2020 to 2024, alongside its breakdown into demand, productivity, inflation, and monetary policy news. The main insight is that of the total 2.70 percentage point increase in the 2-year yield, 2.15 percentage points came on days revealing inflation news. Framed differently, despite only making up 41% of the total number of days over 2020-2024, inflationary news days accounted for 80% of the total rise in the 2-year yield. On these days bond yields and inflation swap rates rose while stock valuations fell, suggesting that markets priced the typical dynamics of a negative supply shock: weaker expected real activity and higher expected inflation.

By contrast, on days with aggregate demand news—when stock prices, bond yields, and inflation swap rates move in the same direction—the 2-year yield remained tame, except for a sharp fall during the fall of Silicon Valley Bank in March 2023. The dominant role of inflationary news over aggregate demand news aligns with the view that markets came to perceive the Fed as shifting to an inflation-focused monetary policy stance in the post-pandemic period Bauer et al. (2024), and that supply-side risks were reflected in the stock-bond comovement once monetary policy was expected to aggressively respond to inflation Pflueger (2025).

Figure 1. 2-year U.S. Treasury Yield during the 2022-2023 Inflation Surge
Decomposition of the cumulative change in the 2-year U.S. Treasury yield (black) into "Demand News" (blue), "Productivity News" (orange), "Inflationary News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is January 2020 to December 2024.



Although a traditional sign-identified SVAR may recover similar insights for the inflationary surge from mid-2021 through 2023, we adopt the CLONE approach because of the several benefits its simplicity offers over the traditional SVAR approaches. In particular, because our classification is exhaustive, we identify four types of news from three markets, whereas sign-restricted SVARs can identify at most three types of structural shocks. Further, we avoid the need to estimate a dynamic model since daily changes in financial market asset prices are unpredictable to a good approximation (Fama, 1970, 1998). Forgoing this estimation further allows us to relax several assumptions regarding variances and covariances, such as mutually uncorrelated shocks and constant variances and covariances over time, which may be too restrictive during periods of rapidly changing market conditions. Finally, because our daily classification is based on the realized combination of asset price changes, it yields a unique and immutable classification each day, avoiding the ambiguities found in sign-identified SVARs in which multiple shock configurations can satisfy the same sign restrictions.

CLONE's simplicity is also its key limitation. Since we identify each day with one news type, we ignore the possibility that certain days can signal more than one news type, and we can attribute noisy days with no news to a given news type. However, if news tends to disperse slowly over time, a bulk of the classification errors average out when we aggregate the daily identification to the monthly or quarterly frequency.[3] In Section IV, we more formally discuss how our assignment of a single news type to each day can be interpreted as inferring the dominant source of news on that day, and how CLONE produces qualitatively similar conclusions as traditional SVARs.

This paper proceeds as follows. Section II introduces the combinations of price changes in stocks, bonds, and inflation swaps that underpin our decomposition. Section III describes the data, documents time-series dynamics, and discusses summary statistics of our decomposition. Section IV compares the results of the shocks decomposition from a benchmark VAR with sign restrictions and with forecast updates from surveys of professional forecasters. Section V highlights applications of CLONE to variance decompositions of asset prices and event studies around FOMC meetings as well as macroeconomic data releases. Section VI offers concluding remarks.

II. From Asset Price Changes to News Types

A. Classification of Daily Returns

We focus our analysis on the U.S. because of the relatively higher liquidity in inflation-linked product markets, which are crucial for our identification.[4]. In particular, we classify each trading day based on the joint dynamics of the S&P 500, the 2-year U.S. Treasury yield, and the 2-year inflation swap rate. Our choice of asset classes is motivated by their close connections to key macroeconomic aggregates. Daily changes in the:

- **S&P 500** is related to news about firms' real earnings growth and, in turn, to GDP growth.

[3] This statement is not inconsistent with the limited predictability of asset returns at short horizons. While daily price changes are difficult to forecast ex ante, macroeconomic news often arrives and is incorporated into prices gradually. As a result, classification errors arising from daily noise tend to average out when the analysis is aggregated to lower frequencies.

[4] In Canada, issuance of inflation-linked government bonds has ceased since 2022, and the inflation swap market never developed into a mature market.

- **2-year U.S. Treasury yield** is related to news about future inflation and the expected path of interest rates.

- **2-year inflation swap rate** is related to news about future inflation expectations.

Table I maps the type of macroeconomic news we infer from each possible joint movement in stocks, bonds, and inflation swaps.

Table I

Identification of Daily News Types

Assumptions used to classify each day as news about the demand, productivity, inflation, and monetary policy news. A "+" denotes a positive change while a "-" denotes a negative change. Signs in brackets indicate the response to negative news: a negative demand news lowers the stock market, inflation swaps, and nominal bond yields. Every day is unambiguously identified with exactly one news type based on these assumptions.

	Demand News	Productivity News	Inflation News	Monetary News
Stock Market	+ (−)	+ (−)	− (+)	− (+)
Inflation Swap	+ (−)	− (+)	+ (−)	− (+)
Nominal Yield	+ (−)	+ (−)	+ (−)	+ (−)

1. **Demand News.** News about stronger future aggregate demand lifts expected earnings growth and the inflation rate. This expectation is captured by higher stock market valuations and higher inflation swap rates. Nominal bond yields also rise because of a combination of higher expected inflation and a tighter expected monetary policy stance.

2. **Productivity News.** Positive productivity news reflects supply-side developments expected to raise future potential output, which lifts expected earnings growth and lowers expected inflation. This pattern emerges from higher stock market valuations and lower inflation swap rates. Interest rates are expected to increase, which lifts bond yields immediately.

3. **Inflationary News.** Positive inflationary news resembles supply-side developments expected to raise firms' input costs, like wages or raw materials. Inflation is expected to rise, and, through the anticipated response of monetary policy, the path of expected interest rates also increases. This pattern is captured by higher inflation swap rates and higher bond

yields. As a result, expected earnings growth is revised down and stock market valuations drop, moving in the opposite direction to both yields and inflation swap rates.

4. **Monetary News.** Monetary news is countercyclical: it is associated with future earnings growth and expected inflation moving in the opposite direction to bond yields. Positive monetary news lifts bond yields, while stock market valuations and inflation swap rates decline together.

There are a few noteworthy observations about this identification approach.

- **Exhaustive Classification.** One key difference of this approach relative to the more common SVAR approaches is that we classify the new information released each day unambiguously into a single category of news. This classification can be interpreted as an informal form of shrinkage. While this shrinkage requires us to discard cases in which multiple news types with partially offsetting effects would generate the same net daily change in asset prices, it allows us to identify up to four distinct types of news from three markets, whereas a sign-identified VAR would identify at most three types of news from three markets.

- **Model-Free Identification.** This approach also leverages the fact that daily price changes are random to a good approximation (Fama, 1970, 1998). This lets us avoid potential model misspecification errors arising from estimating a dynamic system. More importantly, this approach circumvents the set-identification challenges inherent with sign-restricted VAR methods.

- **Risk Premiums.** This approach is silent about the explicit role of risk premiums. In effect, we assume that potential risk premium news, like changes in the equity risk premium or inflation risk premium, is subsumed by and induced by the same co-movement between expected earning growth, expected inflation, and the path of expected interest rates.[5]

B. *Combining News Components Across Asset Classes*

Time t is daily. Let $\Delta P_{i,t}$ be the change from $t-1$ to t for asset $i \in \{s, y, \pi\}$, where s represents the stock market index, y the 2-year yield, and π the 2-year inflation swap rate. Further, let

[5] One way to explicitly consider risk premium news in our framework would be to include changes in the 10-year U.S. Treasury yield, as in Cieslak and Pang (2021). The addition of "common" and "hedging" risk premium news with opposite patterns would entail potentially interpreting 8 possible news types (i.e., demand, productivity, inflation, and monetary news with either a "common" or "hedging" risk premium element). We defer the study of risk premium news to the future.

$\mathbb{1}_t^k$ denote an indicator equal to 1 if the joint price changes satisfy the sign pattern associated with news type k, and 0 otherwise, where $k \in \{D, P, I, M\}$ correspond to demand, productivity, inflation, and monetary news. It follows that we can represent $\Delta P_{i,t}$ as a linear combination of the interaction terms $\Delta P_{i,t}^k = \Delta P_{i,t} \mathbb{1}_t^k$:

$$\begin{aligned} \Delta P_{i,t} &= \Delta P_{i,t}\big(\mathbb{1}_t^D + \mathbb{1}_t^S + \mathbb{1}_t^I + \mathbb{1}_t^M\big) \\ \Delta P_{i,t} &= \Delta P_{i,t}^D + \Delta P_{i,t}^S + \Delta P_{i,t}^I + \Delta P_{i,t}^M \end{aligned} \tag{1}$$

Equation 1 always holds because we classify each day uniquely as one of the four types of news. We aggregate the daily classification to the monthly frequency, which is common in studying the interaction between financial markets and the macroeconomy. If our classification method adds noise, then the time aggregation should sweep some of it aside.

i Define daily dummy variables $\mathbb{1}_t^{k+}$ and $\mathbb{1}_t^{k-}$ for "positive" and "negative" news for each type of economic news.

$$\Delta P_{i,t}^{k+} = \mathbb{1}_t^{k+} \Delta P_{i,t} \quad \text{and} \quad \Delta P_{i,t}^{k-} = \mathbb{1}_t^{k-}$$

ii Sum the signed daily changes within each month m for each asset class. In this way, the monthly news satisfies the sign restrictions across assets by construction.

$$\Delta P_{i,m}^{k+} = \sum_{t \in m} \Delta P_{i,t}^{k+} \quad \text{and} \quad \Delta P_{i,m}^{k-} = \sum_{t \in m} \Delta P_{i,t}^{k-}$$

iii For each news type, and for the negative and positive components $\Delta P_{i,m}^{k+}$ and $\Delta P_{i,m}^{k-}$ separately, compute the first principal component of the three asset $i \in \{s, y, \pi\}$ price monthly changes, with factor loadings $\lambda_{i,+}^k$.

iv The positive and negative monthly news aggregates the monthly price changes as follows:

$$News_m^{k+} = \sum_{i \in \{s,y,\pi\}} \lambda_i^{k+} \, \Delta P_{i,m}^{k+} \quad \text{and} \quad News_m^{k-} = \sum_{i \in \{s,y,\pi\}} \lambda_i^{k-} \, \Delta P_{i,m}^{k-}$$

v Combine the positive and negative components as follows:

$$News_t^k = w_{t,+}^k News_{t,+}^k + w_{t,-}^k News_{t,-}^k$$

where the weights w_t^{k+} and w_t^{k-} are the share days with type k within the month that are positive and negative, respectively.

vi The four monthly $News_t^k$ summarize the information from stocks, bonds, and inflation swaps across news days of type k.

III. Data and Implementation

A. *Data Sources*

We obtain daily data from Bloomberg on the S&P 500 index, the 2-year zero-coupon inflation swap rate, and the 2-year on-the-run U.S. Treasury yield.[6] U.S. inflation swap markets originated in the early 2000s, and so our sample starts in July 2004 and ends in December 2024. We compute the daily changes in the 2-year inflation swap rate, the 2-year U.S. Treasury yield, and the daily log price change of the S&P 500 index (i.e., the daily log return). Finally, we demean the daily log returns of the S&P 500 to remove the average effect of the equity risk premium over time.

B. *Descriptive Statistics*

Figures 2 to 4 report the daily series of the 2-year U.S. Treasury yield, the 2-year inflation swap rate, and the S&P 500 index, respectively (solid dark lines). We overlay the cumulative change of each news type.

[6] The Bloomberg tickers are U.S.GG2YR Index (2-year U.S. Treasury yield), U.S.SWIT2 BGN Curncy (2-year inflation swap rate), SPX Index (S&P 500).

Figure 2. CLONE Decomposition of 2-year Yield

Decomposition of the cumulative change in the 2-year U.S. Treasury yield (black) into "Demand News" (blue), "Productivity News" (orange), "Inflationary News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is July 2004 to December 2024.

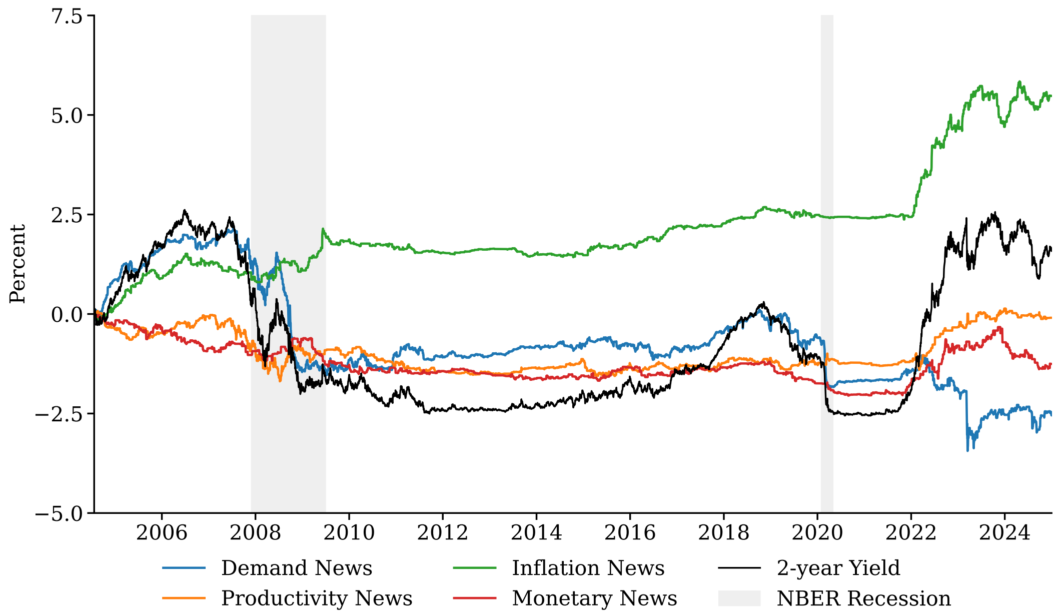


Figure 2 reports the CLONE decomposition for the 2-year yields. Much of the variation during the pre-GFC expansion and during the GFC itself was driven by aggregate demand news. Similarly, aggregate demand news dominated movements in the 2-year yield during the 2018-2019 expansion. In the intervening period, short-term interest rates were at or close to the lower bound and did not vary much. This pattern is consistent with the broader macroeconomic environment at that time: inflation was low and stable near two percent, and with inflation tame, monetary policy was perceived to be more responsive to output.(Bauer et al., 2024)

The other types of news also contribute to yield movements. This is especially apparent after 2022, when inflationary news, productivity news, and monetary news all pushed the 2-year yield up following a prolonged period in which they had little effect. The decomposition attributes the largest share of the post-pandemic increase in yields to inflationary news. In addition to the unsurprising role of the monetary policy news during this period, we also see a contribution of the productivity news, which raised real rates, as evidenced by the concurent decline in the inflation swap rate shown in the next figure.

Figure 3. CLONE Decomposition of 2-year Inflation Swap Rate
Decomposition of the cumulative change in the 2-year Inflation Swap Rate (black) into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is July 2004 to December 2024.

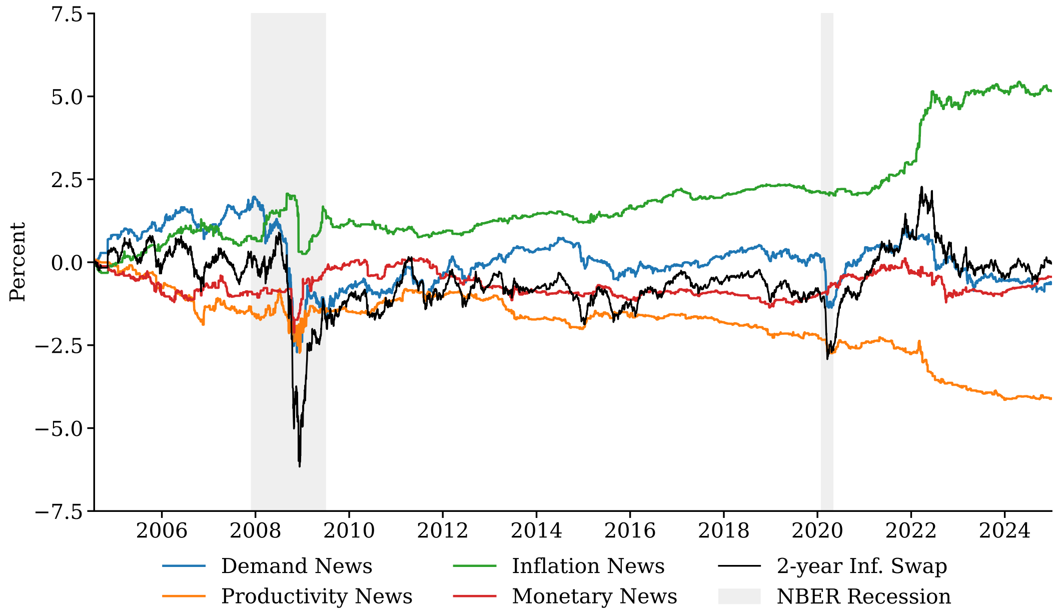


Figure 3 reports the cumulative decomposition of the 2-year inflation swap rate. The cumulative change from 2004 to 2024 is close to zero. However, this hides a gradual increase in the contribution of inflationary news and a corresponding decline in the contribution of productivity news. At higher frequencies, aggregate demand news played a pivotal role in driving the variation in the 2-year inflation swap rate, with the notable exception of the high-inflation episode in 2022. During this period, our classification attributes most the movement in inflation swap rates to inflationary news, and less so to aggregate demand news.

Figure 4. CLONE Decomposition of S&P 500 Index

Decomposition of the cumulative daily log return of the S&P 500 Index (black) into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is July 2004 to December 2024.

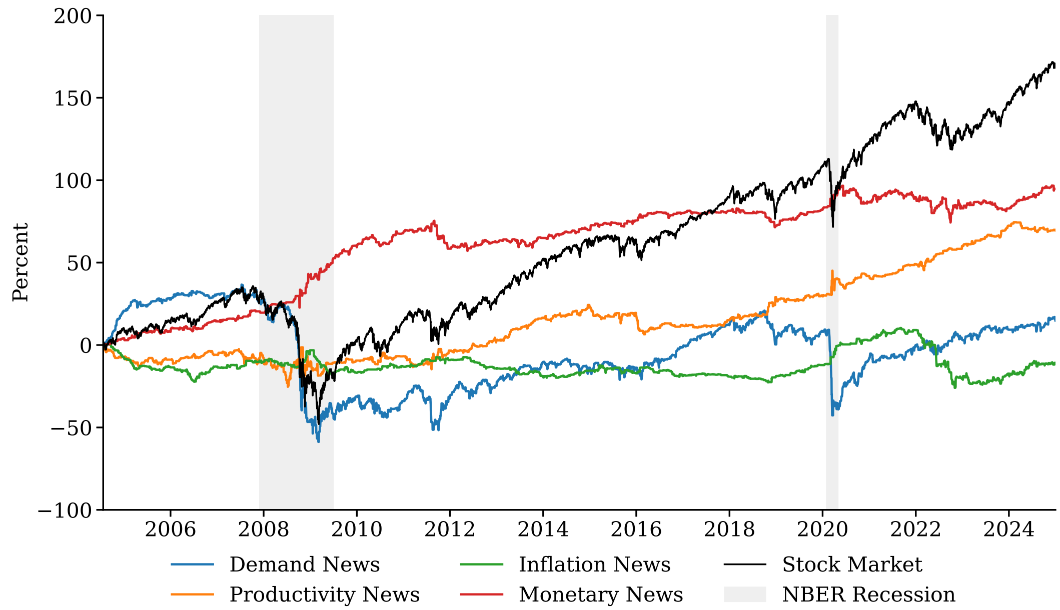


Figure 4 reports the decomposition of the cumulative changes in the S%P 500 index. Our results attribute the fall in the S&P 500 during the GFC and the COVID-19 financial crisis primarily to aggregate demand news. By contrast, the fall in the stock market during the high-inflation period in 2022 is attributed to inflationary news. This distinct response of the S%P 500 is the key reason why inflationary news plays a central role in our decomposition during this period. Finally, much of the long-run upward drift in the S%P 500 is attributed to monetary news early in the sample and to productivity news later in the sample, consistent with the view in Kung and Schmid (2015) that rising confidence in long-run productivity prospects supports equity valuations, echoing the optimism surrounding technological innovation over the 2010s and early 2020s.

C. Variance decomposition

We now turn to higher frequency patterns in our decomposition. Table II presents the extensive margin, reporting the fraction of days in each year that were classified as demand, productivity, inflation, or monetary news. On average, 35% of days in a given year are classified as aggregate demand news, while the remaining days are distributed roughly evenly across the other news types.

This tilt toward demand news is consistent with the fact that much of our sample period overlaps with the post-GFC period, when the U.S. economy was slowly recovering from a deep recession. From a statistical standpoint, the prevalence of demand news in our sample reflects the positive correlation between stock returns and bond yields that persisted from 2000 to 2021 (Duffee, 2023), a pattern commonly attributed to time-varying inflation-output co-movements.(Campbell et al., 2020; Song, 2017). We add to this literature by showing that the positive correlation between stock returns and bond yields is accompanied by a positive correlation with inflation swaps. This helps establish a more direct link with inflation-output co-movements than that implied by the traditional stock-bond correlation alone.

The prevalence of different types of news also varies over time. In particular, the incidence of aggregate demand news declined after 2020, during the COVID-19 crisis and the subsequent recovery, while the role of monetary news—and especially inflationary news—rose sharply.

We further analyze the intensive margin to characterize how markets react on distinct news days. Table III reports summary statistics for demand, productivity, inflation, and monetary news days for the S&P 500 index, the 2-year inflation swap, and the 2-year U.S. Treasury yield. The average changes on days revealing demand news across all three markets are statistically indistinguishable from zero, consistent with a mix of positive and negative demand signals over the past two decades. Across news types, however, the 2-year yield and S&P 500 index exhibit the most pronounced negative skewness on demand news days, likely reflecting the influence of the GFC period.

Productivity and inflationary news days have modest average effects across markets, with the notable exception of the inflation swap market, where large positive kurtosis indicates rare but sizeable spikes in inflation expectations, such as those observed from mid-2021 through 2023. Monetary news has the largest impact on the valuation of the S&P 500 index, whose mean daily return is 10.8 basis points (t-stat=3.3) on these days. This elevated return cannot be attributed solely to scheduled FOMC meetings, as the 1124 monetary news days in our sample far exceed the 140 scheduled FOMC meeting days. This finding underscores the potential importance of the Fed's informal public communications influencing stock market outcomes (Cieslak et al., 2019).

Table II

Summary Statistics, Extensive Margin

This table reports the fraction of days each year for demand, productivity, inflation, and monetary news. For each macro news type, the column "All" represents the total fraction of days per year, the column "(+)" represents the fraction of positive days, and the column "(-)" represents the fraction of negative days. The columns "(+)" and "(-)" sum to "All". Numbers are reported in percent. The sample period is July 2004 to December 2024.

	Demand			Productivity			Inflation			Monetary		
	All	(+)	(-)	All	(+)	(-)	All	(+)	(-)	All	(+)	(-)
2004	31	27	3	25	7	18	24	15	9	21	9	12
2005	29	19	10	22	12	11	23	15	8	26	13	13
2006	28	13	14	23	15	8	25	14	10	24	11	13
2007	33	19	13	28	13	15	20	10	10	20	10	10
2008	41	16	26	28	15	14	17	8	9	14	6	8
2009	41	23	18	17	9	8	20	13	7	22	8	14
2010	44	23	21	18	8	10	17	8	9	21	8	13
2011	38	21	17	23	12	11	18	9	9	21	12	9
2012	35	20	15	23	12	11	18	12	5	24	14	10
2013	29	18	11	22	15	8	21	13	8	28	15	13
2014	35	20	16	20	11	9	21	10	11	24	13	10
2015	35	19	16	23	10	13	25	16	9	18	10	8
2016	41	23	18	16	8	9	23	17	6	20	9	11
2017	36	24	12	22	11	10	21	13	8	21	13	8
2018	42	25	17	20	13	8	19	15	5	18	12	7
2019	39	23	17	22	11	11	20	10	10	18	7	11
2020	43	24	19	18	9	10	14	7	6	25	10	15
2021	28	16	12	15	10	5	24	15	10	33	15	18
2022	28	13	16	16	10	6	30	22	9	25	16	10
2023	35	19	16	19	12	7	28	16	12	18	11	8
2024	27	14	13	13	7	6	39	22	17	21	7	14
N	21	21	21	21	21	21	21	21	21	21	21	21
Mean	35	20	15	21	11	10	22	13	9	22	11	11
Std	6	4	4	4	2	3	5	4	3	4	3	3
Min	27	13	3	13	7	5	14	7	5	14	6	7
P25	29	18	13	18	9	8	19	10	8	20	9	9
P50	35	20	16	22	11	10	21	13	9	21	11	11
P75	41	23	17	23	12	11	24	15	10	24	13	13
Max	44	27	26	28	15	18	39	22	17	33	16	18

Table III

Summary Statistics, Intensive Margin

This table reports summary statistics for daily changes in the 2-year U.S. Treasury yield, Δy, daily changes in the 2-year inflation swap rate, $\Delta\pi$, and daily returns in the S&P 500 index, Δs. The row t-stat tests whether the mean daily change of each macro news component and for each market is statistically different from 0. Numbers are reported in basis points. The sample period is July 2004 to December 2024.

	Demand			Productivity			Inflation			Monetary		
	Δy	$\Delta\pi$	Δs	Δy	$\Delta\pi$	Δs	Δy	$\Delta\pi$	Δs	Δy	$\Delta\pi$	Δs
N	1884	1884	1884	1100	1100	1100	1179	1179	1179	1171	1171	1171
Mean	-0.1	-0.0	0.8	-0.0	-0.4	6.3	0.5	0.4	-0.9	-0.1	-0.0	8.1
t-stat	-1.0	-0.2	0.2	-0.1	-1.6	1.8	3.4	2.3	-0.4	-0.9	-0.2	2.7
Median	0.4	0.3	12.8	0.0	-0.2	7.6	0.0	0.1	0.0	-0.0	0.0	3.2
Std	6.0	7.4	145.3	4.6	7.5	116.3	4.7	6.5	79.0	4.1	6.0	102.0
Skewness	-1.2	0.3	-1.2	0.2	1.3	0.5	0.8	-3.9	0.4	-0.3	0.2	0.8
Kurtosis	15.2	19.5	11.4	5.5	41.6	8.5	7.2	84.7	6.4	7.1	17.3	16.1

IV. External Validity

The simplicity of our CLONE decomposition may raise questions about whether the sign restrictions used to classify asset price movements meaningfully capture the underlying economic news attached to those restrictions. In that respect, this section presents evidence in support of the validity of our identified decomposition. We first examine the persistence of the impact of identified news on asset prices. We then benchmark our decomposition against an alternative based on a sign-restricted SVAR approach. Finally, we relate out identification of news to forecast revisions in survey-based measures of macroeconomic expectations, which are particularly sensitive to the sources of news that our decomposition is designed to capture.

A. Persistence of News

Our identification relies on forward-looking information embedded in financial asset prices. This would indicate that the news components we recover carry information that moves expectations, rather than merely reflect transitory price pressure. We evaluate persistence by running predictive regressions of $t \rightarrow t+h$ changes in asset i on its CLONE components observed on day t, as shown in Equation (2):

$$\Delta P_{i,t\to t+h} = \alpha_{i,h} + \sum_{k\in\{D,P,I,M\}} \beta^k_{i,h} \frac{\Delta P^k_{i,t}}{\sigma^k_i} + v_{i,h}, \tag{2}$$

where we normalize $\Delta P^k_{i,t}$ by its news-specific standard deviations σ^k_i, since the variability of the price changes differs across news types. This normalization is particularly important for the stock market (see Table III). The coefficient of interest $\beta^k_{i,h}$ is the h-day impulse response of asset i to a one standard deviation realization of news type k on day t. A value of $\beta^k_{i,h} > 0$ over long horizons indicates that the identified news component has a persistent—potentially permanent—effect on asset prices.

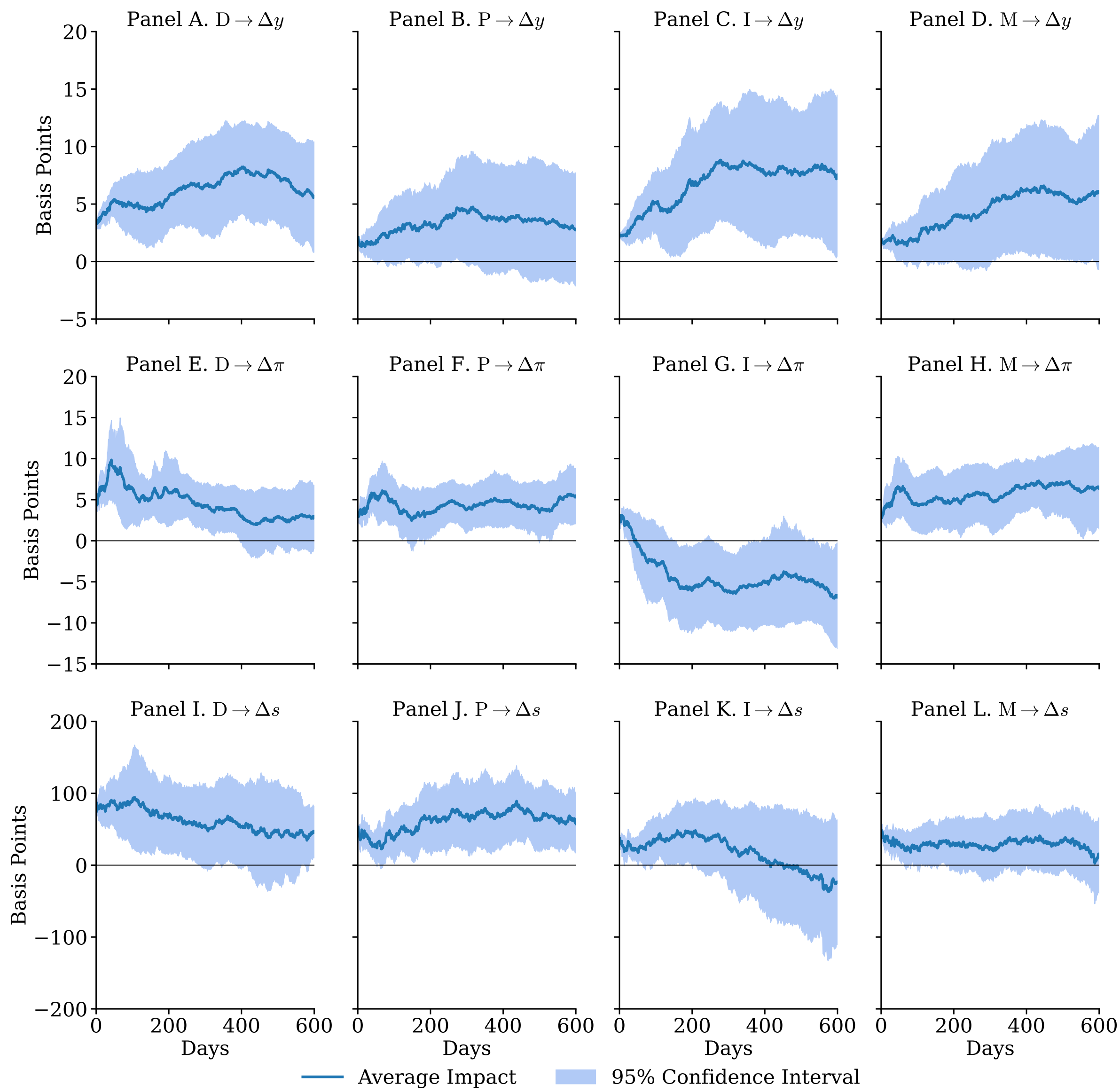
Figure 5 presents the $\beta^k_{i,h}$ coefficients from equation 2 along with 95% confidence bands. Across most cases, we find persistent effects on financial market responses, with point estimates indicating that cumulative effects remain economically meaningful over long horizons. The first column of Figure 5 reports the persistence of the aggregate demand news across bond, stock, and inflation swap markets. We find that effects last for more than one year in each case. We find similar persistence for productivity news, shown in the second column.

A different pattern emerges for inflationary news, shown in the third column. Inflation news has a persistent impact on bond yields; however, the impact on the inflation swap market reverses sign after one to two months, while the impact on the stock market gradually dissipates to zero over the horizon. This pattern may be related to the transitory pattern seen in inflation swaps during the GFC and COVID-19 financial crisis, which has commonly been attributed to illiquidity during these extreme periods of stress.

The main exception is the inflation swap rate's response to inflationary news (Panel G. I $\to$ $\Delta\pi$), which is positive for roughly two months before becoming statistically indistinguishable from zero.

Figure 5. Persistence of News on Asset Prices

The figure shows the $\beta^{k}_{i,h}$ coefficients from equation 2, where i denotes either the S&P 500 index (Δs), the 2-year U.S. Treasury yield (Δy), or the 2-year inflation swap rate ($\Delta\pi$); and k denotes either "Demand News", "Productivity News", "Inflation News", or "Monetary News", as defined in Section II. Each news component, $(\Delta P^{k}_{i,t})$, is standardized to have mean 0 and unit standard deviation. Horizon h is measured in days. Confidence bands are based on Newey-West standard errors with h lags, corresponding to the horizon of the regression. The sample period is July 2004 to December 2024.



B. Relationship to Sign-Restricted SVARs

We next compare our CLONE decomposition approach with a traditional sign-restricted SVAR approach. Identifying news shocks in a VAR has several conceptual advantages over our approach.

The main one can been seen from equation 3

$$u_t = A\epsilon_t \tag{3}$$

which shows that the vector of reduced-form innovations u_t estimated from a VAR is mapped to a vector of structural shocks ϵ_t via the impact matrix B. This mapping implies that, in general, the VAR approach allows multiple sources of news to affect asset prices on a given day. In contrast, our approach imposes a shrinkage structure that identifies a single dominant source of news driving markets on a given day.[7] This form of shrinkage avoids the issue that shocks are only set identified in sign-restricted VAR methods Fry and Pagan (2011). Importantly, shrinking to one type of dominant news also means that we can identify four types of news from these three markets, while the sign-restricted VAR can only identify three types. A formal connection between our CLONE decomposition and sign-restricted SVARs is provided in Section A-I of the Appendix.

We compare CLONE's decomposition with the structural shocks of a sign-restricted VAR, which is estimated following the standard approach from Rubio-Ramirez et al. (2010). Specifically, we estimate a VAR based on daily changes in the (log) of the S&P 500 index, the 2-year U.S. Treasury yield, and the 2-year inflation swap rate.[8] We identify three types of news shocks: aggregate demand, inflationary, and monetary news. The sign restrictions to identify the structural shocks associated with these three sources of news match their CLONE counterparts reported in Table I. Because sign-restricted VARs admit multiple admissible solutions, we follow Fry and Pagan (2011) and select the median-target solution, defined as the rotation whose impulse responses are closest to the median response across draws. We aggregate the resulting daily structural shocks from the SVAR by summing them within each month.

Comparing the SVAR-based structural shocks with the corresponding CLONE news components aggregated across asset classes (as described in Section II), we find that the two approaches are closely aligned. At the monthly frequency, the pairwise correlation coefficients are 0.76 for aggregate demand news, 0.51 for inflationary news, and 0.64 for monetary news.

We further examine the daily concordance between the two approaches at the daily frequency to assess whether our CLONE decomposition produces classifications that differ substantially from those of the sign-restricted VAR. To do so, we compare the daily classifications from the

[7]This amounts to ϵ_t being a vector of zeros except for a single element i equal to 1, and a time-varying impact matrix B_t whose columns are all zero except for column i equal to the daily changes in stocks, bonds, and inflation swaps.

[8]Variables are demeaned prior to estimation and one lag is included in the VAR selected based on the BIC criterion.

two approaches and record how often they assign the same news type on a given day (e.g., both call it a demand day) versus when they differ. For the SVAR-based shocks, we classify each day according to the shock with the largest absolute magnitude. This procedure allows us to track four key outcomes: agreement on "yes" (true positives), agreement on "no" (true negatives), and the two ways they can disagree (false positives and false negatives). From these, we report accuracy (overall agreement), precision (how often our positive calls match the SVAR's), recall (how often we capture the SVAR's positives), and specificity (how often we match the SVAR on negatives).

Table IV shows that the CLONE and the SVAR classifications align on daily news types a large majority of the time, with overall accuracy exceeding 80% across all categories. Agreement is especially strong in precision (70% to 87%) and specificity (84% to 96%), indicating that both approaches are highly consistent in identifying and ruling out most news types. Overall, the results suggest that the two methods yield broadly similar classifications of the dominant source of news on a given day.

The main difference emerges in recall for inflation (52%) and monetary (56%) news, where CLONE captures fewer of the SVAR's positive calls. This gap arises because the SVAR assumes away the role of productivity news that our decomposition treats as a separate category. Moreover, because each day is assigned to the category with the largest absolute contribution, some days that the SVAR labels as monetary or inflationary are instead classified by CLONE as productivity.

Table IV

Concordance Between CLONE and VAR Approaches

This table reports the concordance between CLONE and the sign-restricted SVAR approach along four dimensions. For each day type (demand, inflation, and monetary), we compute: "Accuracy" which is the fraction of days that are either true positives, "TP", (e.g., both approaches classify a day as demand) or true negatives, "TN", (e.g., both approaches do not classify a day as demand); "Precision" which is the number of true positives divided by the number of positive classifications from CLONE (i.e., number of true positives and false positives); "Recall" which is the number of true positives divided by the number of positive classifications from the SVAR approach (i.e., number of true positives and false negatives); and "Specificity" which is the number of true negatives divided by the number of true negative and false negatives. Fractions are reported in percent. The sample period is July 2024 to December 2024.

	Accuracy	**Precision**	**Recall**	**Specificity**
	$\frac{TP+TN}{TP+TN+FP+FN}$	$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$\frac{TN}{TN+FP}$
Demand	81	69	74	84
Inflation	82	84	56	95
Monetary	82	86	56	95

C. *Survey-evidence*

We next relate our identified news components to survey-based macroeconomic expectations, financial conditions, and business conditions. Survey expectations provide a natural benchmark for assessing whether the economic news captured by our decomposition aligns with the information survey participants use to update their economic forecasts. For example, if a given combination of movements in stocks, bonds, and inflation swaps reflects news of stronger aggregate demand, we would expect survey forecasts for real activity and inflation to be revised upward.

Our main source for survey-based expectations is from Blue Chip Economic Indicators (BCEI). We supplement the BCEI survey data with the Federal Reserve's Senior Loan Officer Survey (SLOS) and the National Association of Manufacturers' (NAM) Outlook Survey. These latter two surveys directly capture the views of actual businesses and bank loan officers, allowing us to assess whether CLONE's decomposition summarizes information used by a broad set of economic agents. This broader coverage also helps mitigate concerns that our market-based measures narrowly reflects the views of sophisticated financial market participants and professional forecasters, who are the main respondents in the Blue Chip surveys.

BCEI Survey. We look at a wide range of macroeconomic and financial indicators from the monthly BCEI survey to capture expectations for real activity, inflation, and financial conditions.[9] For a given macroeconomic or financial variable, the BCEI survey collects monthly expectations for quarterly changes (annualized percent changes when applicable) at fixed future calendar quarters.

SLOS Survey. The SLOS survey is conducted by the Federal Reserve Board at a quarterly frequency. The survey cover changes in banks' lending standards and conditions annd loan demand for businesses and households. Specifically, we focus on the net percentage of banks reporting tighter lending standards (banks tightening minus banks easing) over the past three months for large and small firms.[10]

NAM Outlook Survey. The NAM Outlook Survey is a quarterly survey conducted by the National Association of Manufacturers (NAM) to gauge the business outlook of U.S. manufacturers. It provides insights into manufacturers' perceptions of current and future business conditions,

[9] Specifically, for macroeconomic indicators we use real GDP growth, unemployment rate, real disposable income, total CPI inflation, producer price inflation, growth in real personal consumption expenditures (PCE), PCE inflation, industrial production, business inventory growth, and non-residential inventory. For financial indicators we look at expectations for the 3-month interest rate, 10-year yield, AAA credit spread, BAA credit spread, the BAA-AAA spread, and the U.S.D index.

[10] The Federal Reserve's SLOS survey defines large firms as firms with annual sales of $50 million or more, and small firms as those with annual sales of less than $50 million.

including expectations for sales, employment, capital investment, and production.

We examine changes in survey forecasts between periods $t-1$ and t, where forecast updates are quarterly for the SLOS and NAM Outlook Surveys and monthly for the BCEI survey. Because the BCEI survey collects expectations for fixed future calendar quarters rather than a fixed forecast horizon, we compute forecast revisions for the same future calendar quarter over the current quarter and the subsequent three calendar quarters, and sum these revisions to obtain a four-quarter-ahead measure. We then estimate regressions of the form:

$$R_t(Z) = \alpha_0 + \sum_i \alpha_i F_{t-1}^i + \gamma R_{t-1}(Z) + \epsilon_t \tag{4}$$

where $R_t(Z)$ is the total forecast revision for variable Z for the next four calendar quarters as of month t. We regress these forecast revisions on CLONE's lagged monthly composite summary measures F_{t-1}^i, which aggregates news type i across stocks, bonds, and inflation swaps from month $t-2$ to month $t-1$, as described in section II-B. We lag F_{t-1}^i by one month to ensure that the summarized news are part of the information sets of the survey respondents at the time forecasts are formed. We also include a lag of the forecast revision, $\gamma R_{t-1}(Z)$, to account for gradual or sluggish forecast updates.

Table V, VI, and VII reports regression results from (4). We standardize F_{t-1}^i to have zero mean and unit standard deviation over our sample of 2004 to 2024, meaning that their coefficients reflect a 1 standard deviation shift.

Regarding expectations for the macroeconomic outlook, we find that our demand component is positively related to expectations of real activity and inflation, in a statistically significant way for most indicators. A positive one-standard deviation shift in the demand component raises expectations for nearly all real-activity expectations: real GDP (+0.48 percentage points), real PCE (+0.39 percentage points) and industrial production (+0.73 percentage points). Inflation expectations move in tandem, with CPI and PPI inflation forecasts both revised upward by roughly 0.3 percentage points.

Increases in our inflation news component are also associated with positive revisions to CPI and PPI inflation forecasts, of magnitudes similar to those implied by our demand news component, but are accompanied by declines in real disposable income (-0.11 percentage points) and a rise in unemployment expectations (-0.10, though statistically insignificant).

For our monetary news component, a positive shift- reflecting expectations of tighter monetary policy- leads to downward revisions in both inflation expectations (-0.15 percentage points in CPI inflation and -0.44 percentage points in PPI inflation) and lower expected real activity (-0.05 percentage points in real GDP growth, though statistically insignificant, -0.23 percentage points in industrial production, and -0.29 percentage points in non-residential inventories).

By contrast, our productivity-news component exhibits negligible effects on macroeconomic expectations, suggesting that, over the past two decades, these particular co-movements in stocks, bonds, and inflation swaps have not provided sufficiently strong signals about the economic outlook to generate consistent forecast revisions for real activity or inflation.

Turning to financial-variable forecasts, we find that positive shifts in the demand news component are associated with expectations of easing financial conditions. Credit spread forecasts are revised downward, the net share of banks reporting tighter lending standards declines relative to those reporting easing, and the U.S. dollar index is expected to depreciate—consistent with an expected improvement in global risk appetite. Although interest rate expectations also rise following positive demand news, this increase is not enough to offset the overall expected easing in financial conditions reported by survey participants.

By contrast, positive inflation news is historically associated with upward revisions to both short- and long-term nominal interest rate expectations. After netting out revisions to inflation expectations (as reported in Table V), we find that real interest rate expectations remain broadly unchanged in response to positive inflation news. At the same time, bank lending standards are expected to tighten, suggesting that loan officers interpret inflation news as signaling a broad-based contraction in real economic activity.

News of monetary tightening is also correlated with anticipated tightening of financial conditions: interest rate expectations are revised upward, while credit spreads widen and bank lending standards tighten, those these latter effects are not statistically significant at conventional levels.

Finally, we find that our demand and monetary news components are associated with business sentiment in ways conventional theory would posit. In response to positive demand news, businesses broadly report a stronger outlook, with sales, prices, cap-ex, inventory, employment, and wages all rising. Meanwhile, news of tightening monetary policy shows the reverse. Productivity and inflation news have historically not been strongly related with business expectations.

Taken together, these results broadly align with the macroeconomic interpretations underlying CLONE: forecasters systematically revise their views towards an expansionary demand shock when our demand news component rises, towards a cost-push inflationary shock when our inflation news component rises, and toward a monetary tightening when our monetary news component increases.

Table V

Macroeconomic Expectations

This table shows the relationship between revisions in survey forecasts of macroeconomic variables and the first PC for "D" Demand News, "P" Productivity News, "I" Inflation News, and "M" Monetary News. Forecasts are taken from the monthly Blue Chip consensus expectations. Forecast revisions are changes in consensus expectations for the same calendar quarter. Regressions are based on the cumulative change in forecast revisions over the next 4 quarters. Revisions are regressed against the PCs at $t-1$ since surveys take place in the first couple of weeks in a month. PCs are standardized to have unit standard deviation. All regressions include 1 lag of the dependent variable.

	Real GDP (1)	Unemp. Rate (2)	Real Disp. Income (3)	CPI Inflation (4)	Prod. Price Inflation (5)	Real PCE (6)	PCE Inflation (7)	Ind. Production (8)	Business Inventory (9)	Non Res. Inventory (10)
D	0.50***	-0.69	0.21*	0.28***	0.44***	0.38***	0.06	0.78***	13.46*	0.71***
	(0.15)	(0.45)	(0.12)	(0.08)	(0.16)	(0.14)	(0.15)	(0.27)	(8.17)	(0.22)
P	0.06	0.03	0.04	-0.12*	-0.08	0.00	-0.54	0.09	-0.98	-0.72***
	(0.04)	(0.08)	(0.08)	(0.06)	(0.12)	(0.04)	(0.34)	(0.11)	(1.55)	(0.23)
I	-0.04	-0.03	-0.06	0.20***	0.23**	-0.01	0.17***	-0.03	-0.63	-0.11
	(0.05)	(0.05)	(0.06)	(0.05)	(0.09)	(0.06)	(0.04)	(0.10)	(1.68)	(0.07)
M	0.01	-0.20	0.12	-0.06	-0.25**	0.01	0.03	-0.10	4.53	-0.20***
	(0.09)	(0.23)	(0.20)	(0.07)	(0.12)	(0.08)	(0.07)	(0.14)	(4.25)	(0.06)
N	242	242	243	242	242	243	52	242	242	48
R^2	0.43	0.28	0.06	0.53	0.39	0.26	0.37	0.31	0.15	0.56

V. Empirical Applications

This section presents several empirical applications of CLONE to demonstrate its range of uses for policymakers. We begin by assessing the relative importance of different sources of economic news, measured by the extent to which they drive variation in asset prices. We then focus on FOMC meetings and key macroeconomic data releases to identify the nature of information revealed at these events and how it drivers repricing in financial markets.

A. Sub-sample analysis

We begin by quantifying the contributions of each news type to overall asset price variation for stocks, bonds, and inflation swaps. For each asset class, we take the variance of daily price changes attributable to each of the four news components, as described in Equation 5

$$Var(\Delta P_{i,t}) \approx Var(\Delta P^D_{i,t}) + Var(\Delta P^S_{i,t}) + Var(\Delta P^I_{i,t}) + Var(\Delta P^M_{i,t}) \tag{5}$$

Table VI
Financial Conditions Expectations

This table shows the relationship between revisions in survey forecasts of financial variables and the first PC for "D" Demand News, "P" Productivity News, "I" Inflation News, and "M" Monetary News. Columns 1-6 are forecasts taken from the monthly Blue Chip consensus expectations. Columns 7-8 report the percentage of banks tightening minus banks easing credit over the last 3 months taken from the Federal Reserve's quarterly Senior Loan Officer Survey (SLOS). Regressions are based on the cumulative change in forecast revisions over the next 4 quarters. Columns 1-6 take PCs at the monthly frequency, and columns 7-8 take PCs at the quarterly frequency to match the SLOS reporting frequency. PCs are lagged by 1 period. PCs are standardized to have unit standard deviation. All regressions include 1 lag of the dependent variable.

	3M Yield (1)	10Y Yield (2)	AAA-U.S.T Spread (3)	BAA-U.S.T Spread (4)	BAA-AAA Spread (5)	U.S.D Index (6)	Net Bank Credit Tightening (Large Firms) (7)	Net Bank Credit Tightening (Small Firms) (8)
D	0.25^{***}	0.22^{***}	-0.18^{***}	-0.29^{***}	-0.11^{*}	-1.56^{**}	-7.32	-5.89
	(0.06)	(0.05)	(0.04)	(0.09)	(0.06)	(0.62)	(4.81)	(4.04)
P	0.00	0.05	-0.03	0.00	0.03	0.38	-3.83	-4.39^{*}
	(0.06)	(0.04)	(0.02)	(0.04)	(0.03)	(0.61)	(3.05)	(2.62)
I	0.18^{***}	0.22^{***}	-0.02	-0.03	-0.01	0.88^{**}	6.00^{**}	4.84^{**}
	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)	(0.34)	(2.38)	(2.25)
M	0.13^{***}	0.17^{***}	-0.01	-0.00	0.01	0.81^{***}	6.09^{**}	5.92^{**}
	(0.03)	(0.04)	(0.02)	(0.05)	(0.03)	(0.18)	(2.64)	(2.39)
N	242	242	243	243	243	66	78	78
R^2	0.56	0.51	0.25	0.35	0.26	0.45	0.40	0.38

Table VII
Businesses' Expectations

This table shows the relationship between changes in expectations of business conditions from the National Association of Manufacturers' (NAM) Outlook Survey and the first PC for "D" Demand News, "P" Productivity News, "I" Inflation News, and "M" Monetary News. All dependent variables represent expected growth rates over the next 12 months. PCs are taken at a quarterly frequency to match the NAM Outlook Survey and are lagged by 1 quarter. PCs are standardized to have unit standard deviation. All regressions include 1 lag of the dependent variable.

	Outlook Index (1)	Sales (2)	Prod. Price (3)	Capex (4)	Inventory (5)	Employment (6)	Wage (7)
D	3.47^{**}	0.96^{***}	0.23^{**}	0.57^{***}	0.36^{**}	0.44^{***}	0.20^{**}
	(1.50)	(0.34)	(0.12)	(0.20)	(0.16)	(0.17)	(0.08)
P	1.02	-0.05	-0.15^{***}	0.02	-0.07	-0.08	-0.04
	(0.64)	(0.15)	(0.04)	(0.09)	(0.06)	(0.08)	(0.03)
I	-0.08	-0.04	-0.11^{*}	-0.05	-0.11	-0.04	-0.00
	(0.46)	(0.14)	(0.06)	(0.12)	(0.11)	(0.08)	(0.03)
M	-1.10^{**}	-0.27^{*}	-0.11^{***}	-0.10	-0.12	-0.15^{*}	-0.02
	(0.54)	(0.15)	(0.04)	(0.11)	(0.10)	(0.08)	(0.02)
N	79	72	75	75	75	75	75
R^2	0.25	0.42	0.40	0.30	0.29	0.34	0.36

These component-specific variances sum only approximately to the total variance of each asset because of non-zero covariance terms between components. We can safely omit these covariance terms, as they are economically negligible at the daily frequency, accounting for 0.015% to 0.03% of total variance across assets over our 2004-2024 sample period.[11]

Figure 6 reports variance ratios across four sub periods: 2004-2009 covering the period before and including the GFC, 2010-2019 for the period after the GFC during which interest rates remained near their effective lower bounds, 2020 for the period of the COVID-19 financial crisis, and 2021-2024 for the period of elevated inflation.

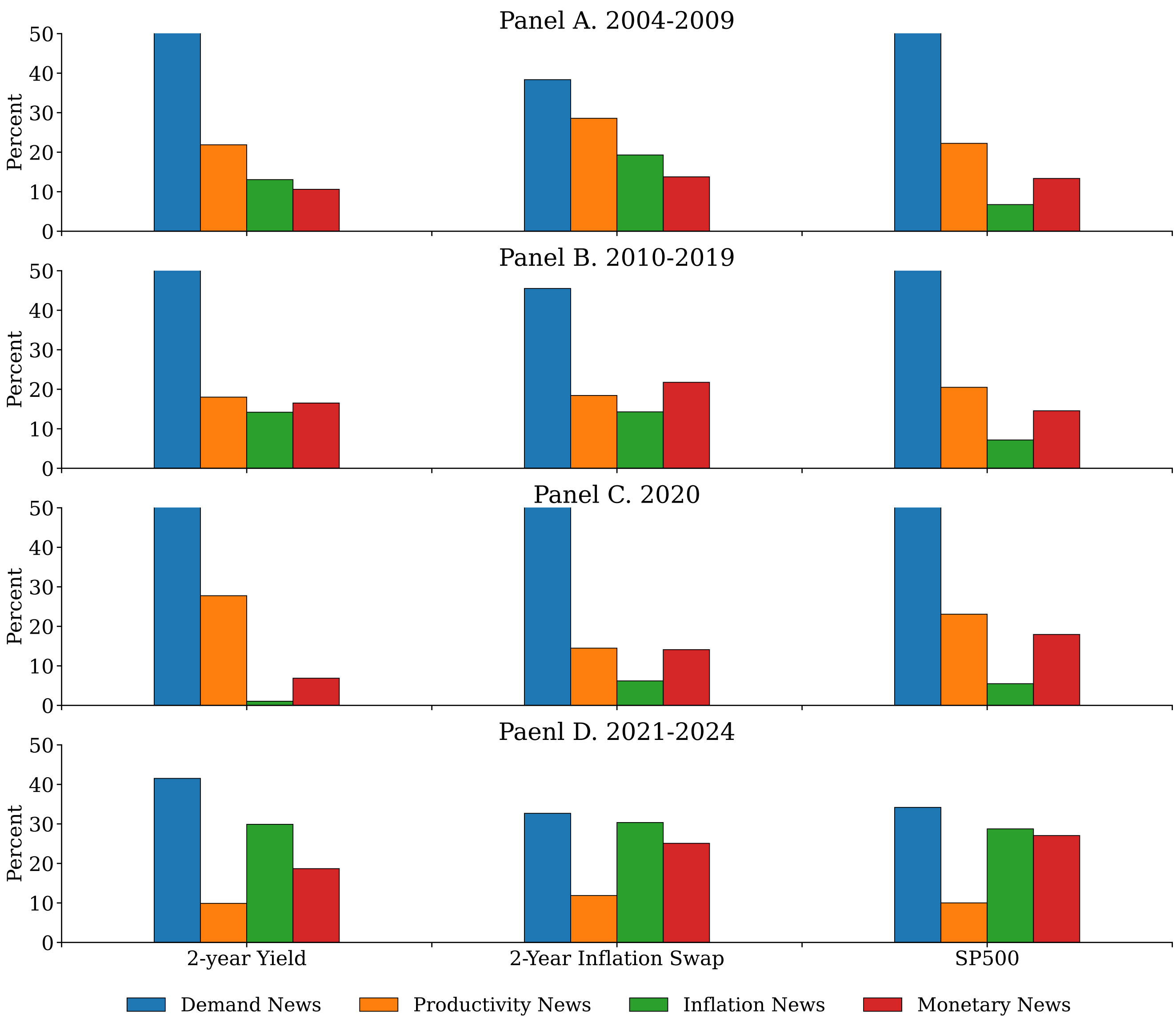
Across asset classes and sub periods, aggregate demand news consistently emerges as the dominant driver of daily asset price variation, accounting for between 30% to 60%, depending on the period and asset class. During 2004-2009, a combination of demand and productivity news explains roughly 70% of the variation in stocks, bonds, and inflation swaps. In the post-GFC period, the contribution of productivity news declined, while monetary news gained importance, highlighting that markets became more sensitive to monetary policy communication in the aftermath of the GFC.

During the COVID-19 shock in 2020, the variance contribution of demand news peaked, reaching 55% to 60% across markets, underscoring that investors primarily repriced assets in response to expectations of a sharp economic contraction followed by recovery. In 2021-2024, markets shifted focus toward inflation and monetary news, with these two components together accounting for slightly more than half of the total asset price variation.

[11] The negligible contribution of these covariance terms arises primarily because CLONE attributes the entire daily change in an asset price to a single dominant news type. Formally, the covariance between the daily change of any two components ΔX and ΔY is $Cov(\Delta X, \Delta Y) = \mathbb{E}[\Delta X \Delta Y] - \mathbb{E}[\Delta X]\mathbb{E}[\Delta Y]$. Under CLONE's decomposition, $\mathbb{E}[\Delta X \Delta Y] = 0$ by construction and $\mathbb{E}[\Delta X]\mathbb{E}[\Delta Y]$ is approximately zero when measured at the daily frequency.

Figure 6. Variance Ratios

The figure shows the variance ratios from equation 5 for the S&P 500 Index, 2-year U.S. Treasury yield, and 2-year inflation swap rate, decomposed into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red), as defined in Section II. Variance ratios are calculated for four sub-samples: 2004-2009 in Panel A, 2010-2019 in Panel B, 2020 in Panel C, and 2021-2024 in Panel D. Variances are calculated based on daily (log) returns for the S&P 500 Index, daily changes in the 2-year U.S. Treasury yield, and daily changes in the inflation swap rate. The sample period is July 2004 to December 2024.



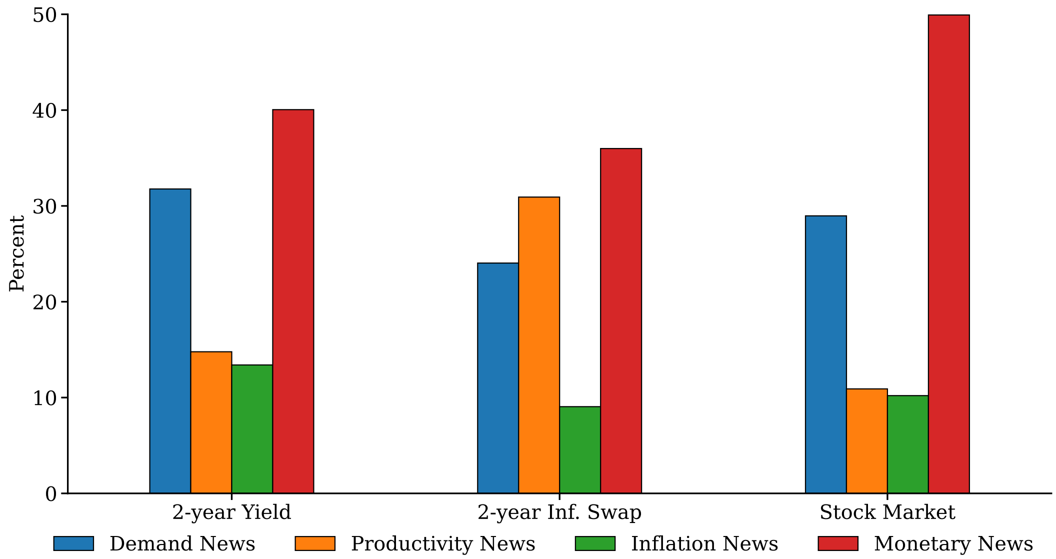
B. FOMC Meetings

A growing body of evidence supports that the Federal Reserve transmits monetary policy through multiple channels. Traditionally, the Fed influences the economy by adjusting administered interest rates to stimulate or restrain inflation and real activity. This mechanism corresponds to CLONE's "monetary news" component. Recently, research has emphasized an "information channel," through which the Fed affects the economy because it possesses information advantages relative to private agents, because its reaction to economic news differs from how private agents expect it to respond (Bauer and Swanson, 2023; Nakamura and Steinsson, 2018). To better understand the nature of information revealed by the Fed, we apply our CLONE decomposition on changes in stocks, bonds, and inflation swaps on days of FOMC meetings.

Figure 7 plots variance contributions of different sources of news across asset prices on the sample of FOMC announcement days. While the sub-sample analysis above highlights the importance of aggregate demand news in driving asset price variation more broadly, variation around FOMC announcements is dominated by monetary news, accounting for between 30% and 60% of the total variance across assets. Such large shares are intuitive given that monetary news aligns with the traditional transmission of monetary policy. At the same time, demand and inflation news also contribute materially to asset price variation, suggesting that investors learn both about the state of the economy and about how the Fed responds to economic signals.

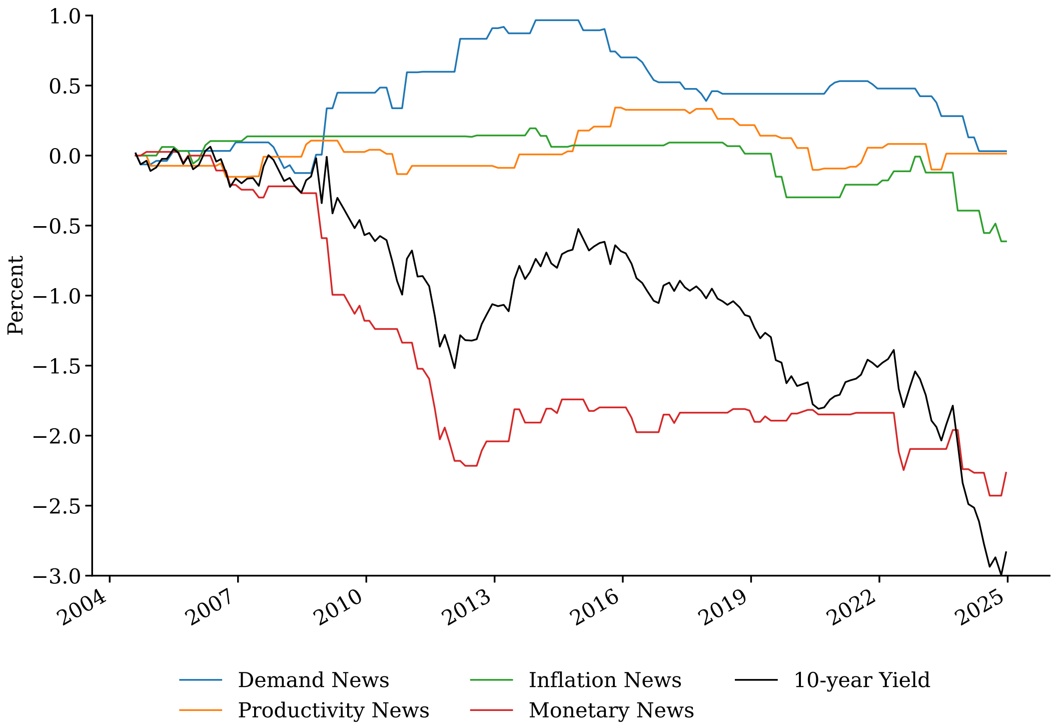
Figure 7. Variance Ratios

The figure shows the variance ratios from equation 5 for the S&P 500 Index, 2-year U.S. Treasury yield, and 2-year inflation swap rate, decomposed into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red), as defined in Section II. Variance ratios are calculated on the sample of scheduled FOMC announcements from July 2004 to December 2024. Variances are calculated based on daily (log) returns for the S&P 500 Index, daily changes in the 2-year U.S. Treasury yield, and daily changes in the inflation swap rate.



Recently, studies have advanced the idea that the Fed reveals information about long-run interest rates at FOMC meetings, either implicitly through adjustments to administered interest rates or explicitly through the release of long-run interest rate projections (Hillenbrand, 2025). The main evidence in support of this view is that changes in long-term U.S. Treasury yields around FOMC meetings closely track the well-documented secular decline in long-term interest rates observed over the past several decades. Given that the underlying economic drivers of these 10-year yield declines around FOMC meetings are not yet well understood, we complement the findings in Hillenbrand (2025) by decomposing these yield changes using CLONE.

Figure 8. CLONE Decomposition of 10-year Yield around FOMC Meetings The figure shows the cumulative sum of the changes in the 10-year yield over a 2-day window around FOMC announcement days, decomposed into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red), as defined in Section II. The sample period is July 2004 to December 2024.



The decomposition in Figure 8 reveals distinct phases in the secular decline of the 10-year yield. From 2008-2012, the downward drift was driven primarily by monetary news, consistent with Hillenbrand's findings that Fed actions and forward-guidance episodes exerted downward pressure on long-term yields during the crisis and early recovery years. Between 2012 and 2015, aggregate demand news pushed in the opposite direction, temporarily raising yields. Thereafter, aggregate demand news again emerged as a dominant contributor to the decline in the 10-year yield.

More recently, beginning in 2023, inflation news has become a more prominent driver of the decline in long-term yields, coinciding with a period in which policy rate hikes led investors to reassess how forcefully the Fed would respond to persistent inflationary pressures Bauer et al. (2024).

Taken together, these results reinforce the view that FOMC announcements convey multiple dimensions of information, underscoring the nuanced and multifaceted signals investors extract from such events.

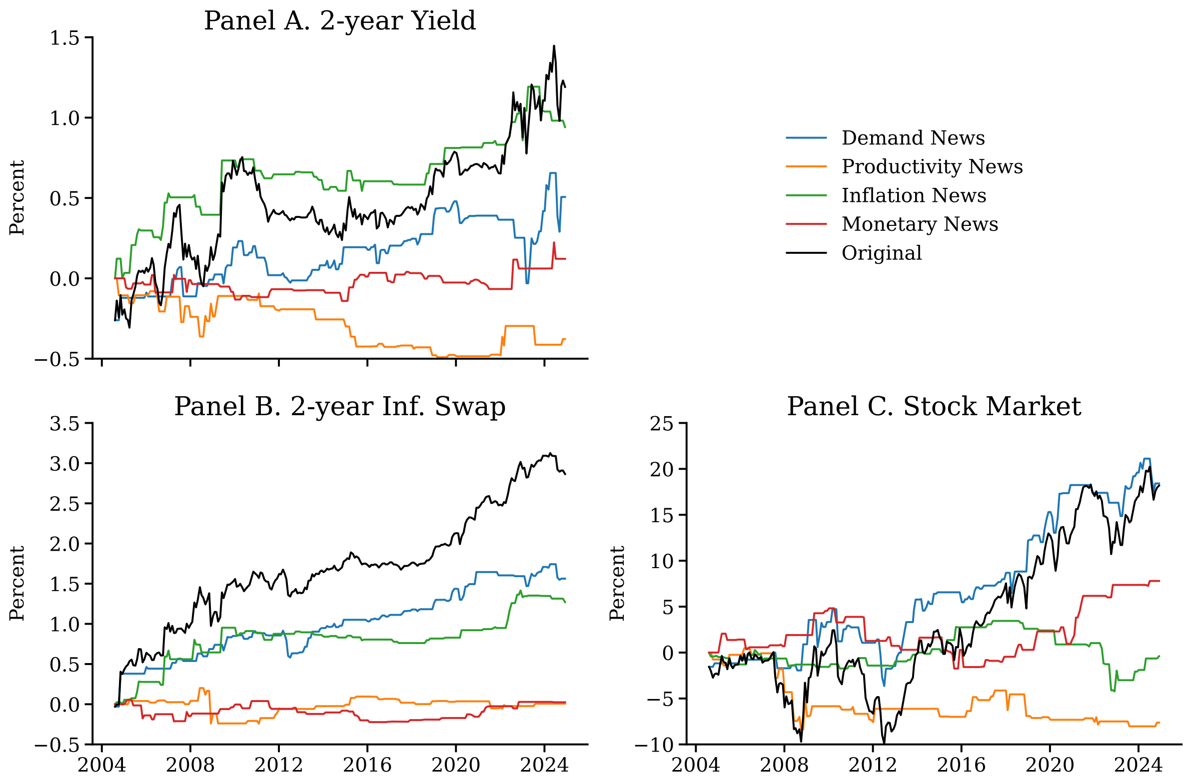
C. *Major Macroeconomic Announcements*

Major U.S. macroeconomic data releases constitute another class of scheduled events closely watched by investors. As with FOMC meetings, the nature of information revealed by these releases is not fully understood. For example, U.S. macroeconomic releases appear not only to convey signals about the trajectory of the economy, but also to be linked to the global financial cycle- the co-movement of capital flows, risky asset prices, credit growth, and leverage (Boehm and Kroner, 2025; Rey, 2013). Following the literature, we focus on two widely watched macroeconomic data releases: the monthly Change in nonfarm Payrolls (labour data) and CPI inflation. As in the previous section, we follow our CLONE decomposition to deconstruct daily changes in stocks, bonds, and inflation swap rates into demand, productivity, inflation, and monetary news. We then cumulatively sum each news component over macroeconomic announcement days, separately for labour and CPI releases.

Figure 9 and 10 report the resulting news decompositions for the S&P 500, the 2-year U.S. Treasury yield, and the 2-year inflation swap rate on days with labour and CPI data releases. For the labour data releases, aggregate demand news is a dominant driver of increases in stocks, bond yields, and inflation swap rates. Inflation news also plays a nontrivial, particularly early in the sample and toward its end. Notably, labour data release days are rarely classified as conveying news about future productivity.

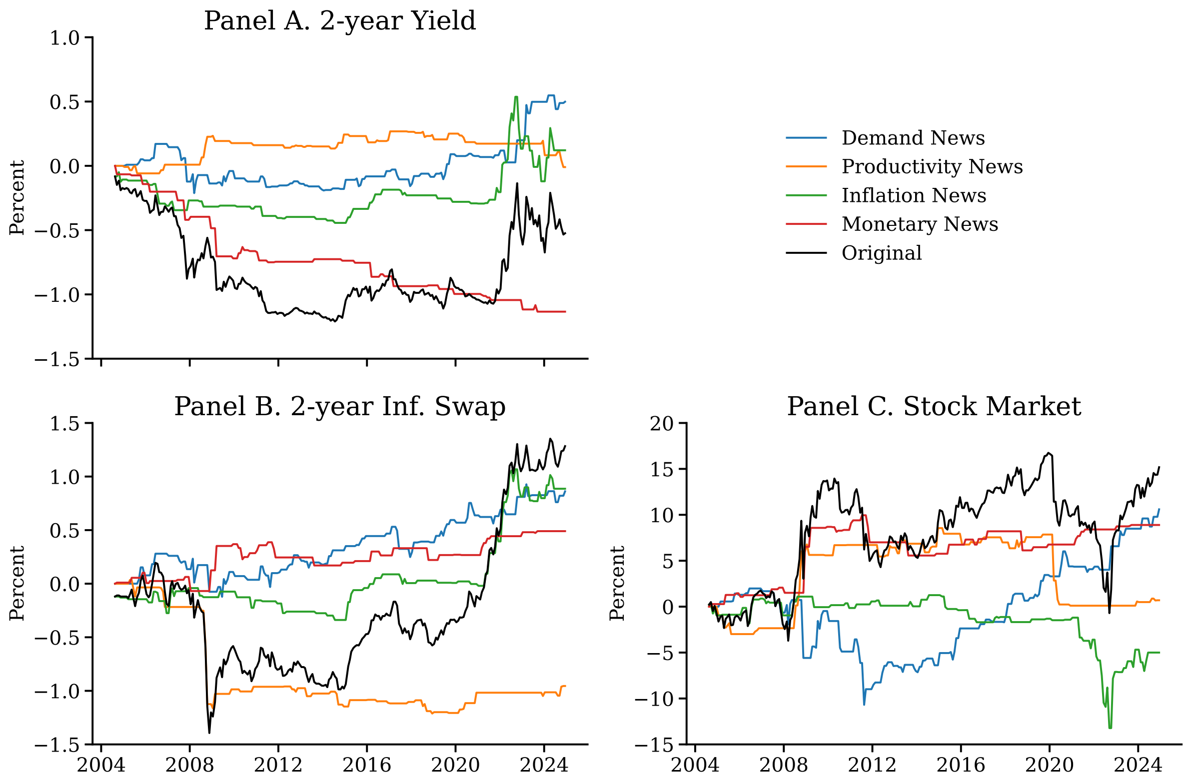
Figure 9. CLONE Decomposition on Labour Data Releases

The figure shows the cumulative change in the 2-year U.S. Treasury yield (Panel A), 2-year inflation swap rate (Panel B), and the S&P 500 (Panel C) on days of U.S. Nonfarm Payrolls data releases. Each asset is decomposed into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is July 2004 to December 2024.



Turning to CPI data releases, we notice a clear shift in the nature of information conveyed, from a mixture of demand, productivity, and monetary news in the pre-2022 period to predominantly inflation news during 2022-2024. In this sense, CPI data releases did not primarily signal demand-driven inflation pressures. Instead, investors interpreted CPI data releases as stagflationary, with stock valuations falling and inflation expectations rising in response to higher-than-expected inflation. This view is consistent with the findings of Knox and Timmer (2025), who show that following CPI data releases, stock prices fall because discount rates increase, while expectations of firms' real earnings fail to keep pace, leaving nominal earnings expectations largely unchanged.

Figure 10. CLONE Decomposition on CPI Data Releases
The figure shows the cumulative change in the 2-year U.S. Treasury yield (Panel A), 2-year inflation swap rate (Panel B), and the S&P 500 (Panel C) on days of U.S. CPI data releases. Each asset is decomposed into "Demand News" (blue), "Productivity News" (orange), "Inflation News" (green), and "Monetary News" (red). Decomposition is defined in Section II. The sample period is July 2004 to December 2024.



Our results can also provide insights into the nature of information revealed by U.S. macroeconomic announcements that transmit to global financial markets Boehm and Kroner (2025). While that literature relies on stock-bond return correlations to distinguish between the role of news about interest rates (negative correlation) and real activity (positive correlation) in the global transmission of U.S. shocks, CLONE exploits additional information from the inflation swap market, allowing us to classify news into finer categories.

Separately for U.S. CPI and labour data releases, we estimate country-specific regressions of the form:

$$r_{c,t} = \omega_c + \sum_{k \in \{D,S,I,M\}} \gamma_{c,k} \Delta P^k_{s,t} + v_{c,t} \tag{6}$$

where $r_{c,t}$ is the return of country c's stock market on announcement day t, and $\gamma_{c,k}$ captures country c's sensitivity to the U.S. stock market return, conditional on whether the CPI or labour release on day t reveals demand, productivity, inflation, or monetary news ($\Delta P_{s,t}^{k}$). We estimate sensitivities with respect to the U.S. stock market return, rather than to announcement surprises, to facilitate interpretation. Under the assumption that the U.S. macroeconomic release is, on average, the the dominant driver of the stock market's movements on that day, a $\gamma_{c,k} = 1$ can be interpreted as a full pass-through of the news revealed by the announcement to country c's stock market.

Table VIII reports the regression results from Equation 6. Consistent with the findings of Boehm and Kroner (2025) that nonfarm payroll surprises propagate internationally through news about real activity, we show that G10 stock markets co-move strongly with the U.S. stock market when labour data releases reveal aggregate demand or productivity news. Notably, return sensitivities across the G10 countries are consistently larger on productivity news days than on demand news days, with a median sensitivity of 0.36 on demand news days and a median sensitivity of 0.78, more than double on productivity news days.

On days with CPI data releases, the pattern of transmission to global stock markets differs markedly across news types. In contrast to labour data releases, where demand news dominates, CPI data releases reveal an additional strong role for inflation news. Global stock markets are more sensitive to CPI data releases interpreted as productivity news than to those interpreted as demand news. Across G10 countries, the estimated coefficients for productivity news are consistently larger than those for demand news, with the median coefficient of 0.97 for inflation news, compared with 0.51 for demand news. This asymmetry suggests that CPI data releases interpreted as "bad" inflation news-that is, news that moves growth and inflation in opposing directions-transmits more strongly to global stock markets than CPIE releases interpreted as "good" inflation news-the kind that moves growth and inflation in the same direction.

Table VIII

G10 Stock Markets and Labour Data Releases

This table reports regression results from equation 6, in which daily G10 stock market returns are regressed on daily U.S. stock market returns on days with U.S. Nonfarm Payrolls releases. U.S. stock market returns are decomposed into returns on days classified as "Demand News" ($\Delta P^D_{s,t}$), "Productivity News" ($\Delta P^S_{s,t}$), "Inflation News" ($\Delta P^I_{s,t}$), and "Monetary News" ($\Delta P^M_{s,t}$). Numbers in brackets report Newey-West standard errors. The sample period is July 2004 to December 2024.

	AUD (1)	CAD (2)	CHF (3)	EUR (4)	GBP (5)	JPY (6)	NOK (7)	NZD (8)	SEK (9)
$\Delta P^D_{s,t}$	0.57***	0.22	0.28***	0.32***	0.28***	0.88***	0.45***	0.24***	0.35***
	(0.10)	(0.15)	(0.08)	(0.11)	(0.10)	(0.19)	(0.14)	(0.08)	(0.08)
$\Delta P^P_{s,t}$	0.76***	0.62**	0.71***	0.60**	0.69**	0.78***	1.16**	0.37***	1.12***
	(0.14)	(0.29)	(0.21)	(0.23)	(0.29)	(0.13)	(0.45)	(0.11)	(0.37)
$\Delta P^I_{s,t}$	0.22	0.01	0.21	0.02	0.01	-0.04	0.15	0.44***	0.28
	(0.25)	(0.26)	(0.17)	(0.31)	(0.21)	(0.21)	(0.23)	(0.09)	(0.30)
$\Delta P^M_{s,t}$	0.16	-0.15	0.22	0.29	0.14	0.24**	0.15	-0.09	0.21
	(0.17)	(0.12)	(0.27)	(0.34)	(0.28)	(0.12)	(0.36)	(0.07)	(0.40)
N	245	245	245	245	245	245	245	245	245
R^2	0.28	0.11	0.19	0.10	0.12	0.28	0.19	0.22	0.20

Panel B. U.S. CPI Data Releases

	AUD (1)	CAD (2)	CHF (3)	EUR (4)	GBP (5)	JPY (6)	NOK (7)	NZD (8)	SEK (9)
$\Delta P^D_{s,t}$	0.68***	0.51*	0.45***	0.34***	0.33***	0.75***	0.35***	0.29***	0.26***
	(0.05)	(0.27)	(0.08)	(0.08)	(0.09)	(0.09)	(0.13)	(0.06)	(0.08)
$\Delta P^P_{s,t}$	0.57	1.09**	1.01***	0.89**	1.08***	0.76***	0.91***	0.58***	0.97*
	(0.36)	(0.55)	(0.28)	(0.40)	(0.37)	(0.06)	(0.34)	(0.15)	(0.53)
$\Delta P^I_{s,t}$	0.58***	0.09	0.14**	0.23**	0.10	0.57***	0.23	0.34***	0.22***
	(0.07)	(0.08)	(0.07)	(0.09)	(0.08)	(0.11)	(0.16)	(0.06)	(0.07)
$\Delta P^M_{s,t}$	0.23**	0.14	0.07	0.21	0.22**	0.17***	0.59***	0.05	0.25*
	(0.09)	(0.12)	(0.07)	(0.13)	(0.09)	(0.06)	(0.15)	(0.07)	(0.14)
N	245	245	245	245	245	245	245	245	245
R^2	0.47	0.29	0.36	0.24	0.31	0.47	0.18	0.42	0.20

VI. Conclusion

We introduce CLONE, a simple and transparent decomposition of asset price movements. CLONE classifies the type of macroeconomic news revealed from stocks, bond yields, and inflation swap rates. The news components identified by CLONE exhibit persistent effects on asset prices, produce qualitatively similar conclusions to those obtained from sign-restricted SVARs, and align well with revisions in professional forecasters' and businesses' expectations of macroeconomic and financial variables in the direction we would expect.

We show that aggregate demand news accounts for the largest share of daily variation in the S&P 500, the 2-year U.S. Treasury yield, and the 2-year inflation swap rate over 2004–2024. More recently, between 2021 and 2024, the importance of inflation and monetary news increased markedly, reflecting a shift in the dominant drivers of asset price movements.

Finally, we examine the information content of FOMC announcements and major U.S. macroeconomic data releases. While FOMC communications are traditionally associated with monetary policy news, they have increasingly conveyed information about inflation in recent years. At the same time, we find that productivity-related news plays a central role in explaining stock market returns and movements in inflation swap rates, highlighting an additional and often underappreciated dimension of information revealed at policy and data announcements.

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Appendix

A-I. Theoretical Relationship Between CLONE and SVAR

A. The setup

We start with 3 innovations, stacked in a vector $\underbrace{u_t}_{3\times 1}$. The 3 elements of u_t are correlated, and following the sign-restriction SVAR literature, we write u_t, as following:

$$\underbrace{u_t}_{3\times 1} = \underbrace{A}_{3\times 3}\underbrace{\varepsilon_t}_{3\times 1}$$

where

$$sign\,(A) = \begin{bmatrix} + & + & + \\ + & - & - \\ + & - & + \end{bmatrix}$$

and the 3 elements of are ε_t uncorrelated. ε_t is interpreted as a set of structural innovations.

Our classification (CLONE) assumes no lag-structure in the vector of daily asset price changes, Δp_t, implying that $\Delta p_t = u_t$. CLONE then breaks down u_t according to the different possible signs of its elements:

$$u_t = |s_{1t}|\, u_t + |s_{2t}|\, u_t + |s_{3t}|\, u_t + |s_{4t}|\, u_t$$

where

$$s_{1t} = 1_{[u_{1t}>0]}1_{[u_{2t}>0]}1_{[u_{3t}>0]} - 1_{[u_{1t}<0]}1_{[u_{2t}<0]}1_{[u_{3t}<0]} \quad (7)$$

$$s_{2t} = 1_{[u_{1t}>0]}1_{[u_{2t}<0]}1_{[u_{3t}<0]} - 1_{[u_{1t}<0]}1_{[u_{2t}>0]}1_{[u_{3t}>0]} \quad (8)$$

$$s_{3t} = 1_{[u_{1t}>0]}1_{[u_{2t}<0]}1_{[u_{3t}>0]} - 1_{[u_{1t}<0]}1_{[u_{2t}>0]}1_{[u_{3t}<0]} \quad (9)$$

$$s_{4t} = 1_{[u_{1t}>0]}1_{[u_{2t}>0]}1_{[u_{3t}<0]} - 1_{[u_{1t}<0]}1_{[u_{2t}<0]}1_{[u_{3t}>0]}$$

$$|s_{1t}| + |s_{2t}| + |s_{3t}| + |s_{4t}| = 1$$

$$|s_{it}|\,|s_{jt}| = 0, \cdots i \neq j$$

B. Linking the correlation matrix of u_t to the sign probability

Under the Gaussian assumption, and denoting ρ_{ij} the correlation between element i and j of u_t, we can easily establish that:

$$\rho_{12} = -\sin\left(\pi\left(\Pr\left[|s_{2t}| = 1\right] + \Pr\left[|s_{3t}| = 1\right] - \frac{1}{2}\right)\right) \tag{10}$$

$$\rho_{13} = \sin\left(\pi\left(\Pr\left[|s_{1t}| = 1\right] + \Pr\left[|s_{3t}| = 1\right] - \frac{1}{2}\right)\right) \tag{11}$$

$$\rho_{23} = \sin\left(\pi\left(\Pr\left[|s_{1t}| = 1\right] + \Pr\left[|s_{2t}| = 1\right] - \frac{1}{2}\right)\right)$$

and

$$\Pr\left[|s_{1t}| = 1\right] = \frac{1}{4} + \frac{1}{2\pi}\left(\sin^{-1}\rho_{12} + \sin^{-1}\rho_{13} + \sin^{-1}\rho_{23}\right) \tag{12}$$

$$\Pr\left[|s_{2t}| = 1\right] = \frac{1}{4} - \frac{1}{2\pi}\left(\sin^{-1}\rho_{13} + \sin^{-1}\rho_{12} - \sin^{-1}\rho_{23}\right) \tag{13}$$

$$\Pr\left[|s_{3t}| = 1\right] = \frac{1}{4} - \frac{1}{2\pi}\left(\sin^{-1}\rho_{12} - \sin^{-1}\rho_{13} + \sin^{-1}\rho_{23}\right)$$

This implies a mapping between the probabilities $\Pr\left[|s_{it}| = 1\right]$ and the correlation ρ_{ij}. Hence, $\Pr\left[|s_{it}| = 1\right]$ can be used to identify parameters of an SVAR.

C. Linking s_{it} to the ε_t

Intuitively, there should be a link between our classification and the structural shocks ε_t. In particular, we expect $|s_{1t}| = 1$ to occur when ε_{1t} (the first element of ε_t) is "dominant". We now establish that formally. To do that, we assume that ε_t is iid Gaussian and denoted by A_{ij} the elements of A.

Proposition 1. *$s_{1t} = 1$ if and only if $\varepsilon_{1t} > \bar{\varepsilon}_{1t}$, where*

$$\bar{\varepsilon}_{1t} \equiv -\min\left(\frac{A_{12}}{A_{11}}\varepsilon_{2t} + \frac{A_{13}}{A_{11}}\varepsilon_{3t}, \frac{A_{22}}{A_{21}}\varepsilon_{2t} + \frac{A_{23}}{A_{21}}\varepsilon_{3t}, \frac{A_{32}}{A_{31}}\varepsilon_{2t} + \frac{A_{33}}{A_{31}}\varepsilon_{3t}\right)$$

In other words, $s_{1t} = 1$ occurs when ε_{1t} is large and positive. Furthermore, we can show that the threshold $\bar{\varepsilon}_{1t}$ is most likely positive, indeed we have

$$\Pr\left[\bar{\varepsilon}_{1t} > 0\right] = \frac{7}{8} - \frac{1}{4\pi}\left(\sin^{-1}\rho_{12}^{(1)} + \sin^{-1}\rho_{13}^{(1)} + \sin^{-1}\rho_{23}^{(1)}\right)$$

where

$$\rho_{12}^{(1)} \equiv \frac{A_{12}A_{22}+A_{13}A_{23}}{\sqrt{A_{12}^2+A_{13}^2}\sqrt{A_{22}^2+A_{23}^2}} < 0; \rho_{13}^{(1)} \equiv \frac{A_{12}A_{32}+A_{13}A_{33}}{\sqrt{A_{12}^2+A_{13}^2}\sqrt{A_{32}^2+A_{33}^2}}; \rho_{23}^{(1)} \equiv \frac{A_{22}A_{32}+A_{23}A_{33}}{\sqrt{A_{22}^2+A_{23}^2}\sqrt{A_{32}^2+A_{33}^2}}$$

which establish that $\Pr[\bar{\varepsilon}_{1t} > 0] \approx 1$.

Proposition 2. $s_{1t} = -1$ *if and only if* $\varepsilon_{1t} < \underline{\varepsilon}_{1t}$, *where*

$$\underline{\varepsilon}_{1t} \equiv -\max\left(\frac{A_{12}}{A_{11}}\varepsilon_{2t} + \frac{A_{13}}{A_{11}}\varepsilon_{3t}, \frac{A_{22}}{A_{21}}\varepsilon_{2t} + \frac{A_{23}}{A_{21}}\varepsilon_{3t}, \frac{A_{32}}{A_{31}}\varepsilon_{2t} + \frac{A_{33}}{A_{31}}\varepsilon_{3t}\right)$$

In other words, $s_{1t} = -1$ occurs when ε_{1t} is large and negative. Furthermore, we can show that the threshold $\underline{\varepsilon}_{1t}$ is most likely negative, indeed we have

$$\Pr[\underline{\varepsilon}_{1t} < 0] = \Pr[\bar{\varepsilon}_{1t} > 0] \approx 1$$

Proposition 3. $s_{2t} = 1$ *if and only if* $\varepsilon_{2t} > \bar{\varepsilon}_{2t}$, *where*

$$\bar{\varepsilon}_{2t} \equiv -\min\left(\frac{A_{11}}{A_{12}}\varepsilon_{1t} + \frac{A_{13}}{A_{12}}\varepsilon_{3t}, \frac{A_{21}}{A_{22}}\varepsilon_{1t} + \frac{A_{23}}{A_{22}}\varepsilon_{3t}, \frac{A_{31}}{A_{32}}\varepsilon_{1t} + \frac{A_{33}}{A_{32}}\varepsilon_{3t}\right)$$

In other words, $s_{2t} = 1$ occurs when ε_{2t} is large and positive. Furthermore, we can show that the threshold $\bar{\varepsilon}_{2t}$ is most likely positive, indeed we have

$$\Pr[\bar{\varepsilon}_{2t} > 0] = \frac{7}{8} - \frac{1}{4\pi}\left(-\sin^{-1}\rho_{12}^{(2)} - \sin^{-1}\rho_{13}^{(2)} + \sin^{-1}\rho_{23}^{(2)}\right)$$

where

$$\rho_{12}^{(2)} \equiv \frac{A_{11}A_{21}+A_{13}A_{23}}{\sqrt{A_{11}^2+A_{13}^2}\sqrt{A_{21}^2+A_{23}^2}}; \rho_{13}^{(2)} \equiv \frac{A_{11}A_{31}+A_{13}A_{33}}{\sqrt{A_{11}^2+A_{13}^2}\sqrt{A_{31}^2+A_{33}^2}} > 0; \rho_{23}^{(2)} \equiv \frac{A_{21}A_{31}+A_{23}A_{33}}{\sqrt{A_{21}^2+A_{23}^2}\sqrt{A_{31}^2+A_{33}^2}}$$

which establish that $\Pr[\bar{\varepsilon}_{2t} > 0] \approx 1$.

Proposition 4. $s_{2t} = -1$ *if and only if* $\varepsilon_{2t} < \underline{\varepsilon}_{2t}$, *where*

$$\underline{\varepsilon}_{2t} \equiv -\max\left(\frac{A_{11}}{A_{12}}\varepsilon_{1t} + \frac{A_{13}}{A_{12}}\varepsilon_{3t}, \frac{A_{21}}{A_{22}}\varepsilon_{1t} + \frac{A_{23}}{A_{22}}\varepsilon_{3t}, \frac{A_{31}}{A_{32}}\varepsilon_{1t} + \frac{A_{33}}{A_{32}}\varepsilon_{3t}\right)$$

In other words, $s_{2t} = -1$ occurs when ε_{2t} is large and negative. Furthermore, we can show that the threshold $\underline{\varepsilon}_{2t}$ is most likely negative, indeed we have

$$\Pr[\underline{\varepsilon}_{2t} < 0] = \Pr[\bar{\varepsilon}_{2t} > 0] \approx 1$$

Proposition 5. *$s_{3t} = 1$ if and only if $\varepsilon_{3t} > \bar{\varepsilon}_{3t}$, where*

$$\bar{\varepsilon}_{3t} \equiv -\min\left(\frac{A_{11}}{A_{13}}\varepsilon_{1t} + \frac{A_{12}}{A_{13}}\varepsilon_{2t}, \frac{A_{21}}{A_{23}}\varepsilon_{1t} + \frac{A_{22}}{A_{23}}\varepsilon_{2t}, \frac{A_{31}}{A_{33}}\varepsilon_{1t} + \frac{A_{32}}{A_{33}}\varepsilon_{2t}\right)$$

In other words, $s_{3t} = 1$ occurs when ε_{3t} is large and positive. Furthermore, we can show that the threshold $\bar{\varepsilon}_{3t}$ is most likely positive, indeed we have

$$\Pr\left[\bar{\varepsilon}_{3t} > 0\right] = \frac{7}{8} - \frac{1}{4\pi}\left(-\sin^{-1}\rho_{12}^{(3)} + \sin^{-1}\rho_{13}^{(3)} - \sin^{-1}\rho_{23}^{(3)}\right)$$

where

$$\rho_{12}^{(3)} \equiv \frac{A_{11}A_{21} + A_{12}A_{22}}{\sqrt{A_{11}^2 + A_{12}^2}\sqrt{A_{21}^2 + A_{22}^2}}; \rho_{13}^{(3)} \equiv \frac{A_{11}A_{31} + A_{12}A_{32}}{\sqrt{A_{11}^2 + A_{12}^2}\sqrt{A_{31}^2 + A_{32}^2}}; \rho_{23}^{(3)} \equiv \frac{A_{21}A_{31} + A_{22}A_{32}}{\sqrt{A_{21}^2 + A_{22}^2}\sqrt{A_{31}^2 + A_{32}^2}} > 0$$

which establish that $\Pr\left[\bar{\varepsilon}_{3t} > 0\right] \approx 1$.

Proposition 6. *$s_{3t} = -1$ if and only if $\varepsilon_{3t} < \underline{\varepsilon}_{3t}$, where*

$$\underline{\varepsilon}_{3t} \equiv -\max\left(\frac{A_{11}}{A_{13}}\varepsilon_{1t} + \frac{A_{12}}{A_{13}}\varepsilon_{2t}, \frac{A_{21}}{A_{23}}\varepsilon_{1t} + \frac{A_{22}}{A_{23}}\varepsilon_{2t}, \frac{A_{31}}{A_{33}}\varepsilon_{1t} + \frac{A_{32}}{A_{33}}\varepsilon_{2t}\right)$$

In other words, $s_{3t} = -1$ occurs when ε_{3t} is large and negative. Furthermore, we can show that the threshold $\underline{\varepsilon}_{3t}$ is most likely negative, indeed we have

$$\Pr\left[\underline{\varepsilon}_{3t} < 0\right] = \Pr\left[\bar{\varepsilon}_{3t} > 0\right] \approx 1$$