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Monetary Policy Transmission from the U.S. Federal Reserve to the NASDAQ-100 (2020–2024)

Author: **Israe Bakkali Dhachour**
Supervisor: **Dr. James Thewissen**
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Master [120] in Management, professional focus
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Abstract

This thesis examines the transmission of U.S. monetary policy shocks to the NASDAQ-100 over the 2020–2024 period using three complementary empirical exercises: a high-frequency event study, a Local Projections-IV framework, and a Campbell–Ammer return decomposition. Identification follows Jaroćiński and Karadi (2020), whose sign-based procedure separates pure monetary policy shocks from central bank information shocks within narrow FOMC announcement windows.

A one-standard-deviation contractionary surprise is associated with a -8.40% decrease within the announcement window ($p = 0.008$, $R^2 = 0.291$, $N = 40$). The forward-guidance component drives this response: the path factor coefficient is -12.63% ($p = 0.012$) while the target factor is statistically indistinguishable from zero. Local Projections-IV estimates a cumulative impact of -25.3% per percentage-point increase in the federal funds rate ($p = 0.006$), compared to -10.2% ($p = 0.239$) when the raw unpurified surprise is used as instrument, suggesting that identification discipline matters quantitatively. Pure monetary tightening events generate average same-day NASDAQ-100 returns of -0.20% against $+0.24\%$ for central bank information events ($t = -2.52$, $p = 0.016$). The Campbell–Ammer decomposition finds no statistically significant association between the purified shock and any individual news component — cash-flow news ($p = 0.831$), discount-rate news ($p = 0.803$), and equity risk premium news ($p = 0.426$) — leaving channel attribution inconclusive at the monthly frequency. This result is broadly consistent with the identification framework: purifying the shock removes the artefactual covariation that inflates the apparent equity risk premium channel in studies using raw surprises.

Keywords: monetary policy transmission, NASDAQ-100, high-frequency identification, Jarociński–Karadi, local projections, Campbell–Ammer, central bank information shocks.

1 Introduction

Monetary policy shapes financial markets through multiple and interacting channels. Changes in policy rates, forward guidance, and central bank communication affect equity valuations through revisions in discount rates, expected risk premia, and beliefs about future economic activity. Understanding how these effects operate is central to both macroeconomic analysis and financial valuation, yet the empirical identification of genuine policy shocks remains a persistent challenge: central bank announcements convey not only a change in the policy stance but also the Federal Reserve's private assessment of economic conditions, and these two signals move equity prices in opposite directions.

The post-COVID period provides an unusually informative laboratory for studying this transmission mechanism. Following the outbreak of the pandemic in early 2020, the Federal Reserve cut the federal funds rate to the effective lower bound and deployed large-scale asset purchases alongside extensive forward guidance. Beginning in March 2022, the stance reversed sharply, with eleven consecutive rate increases totalling 525 basis points over eighteen months in response to elevated inflation. This rapid transition from prolonged accommodation to the most aggressive tightening cycle in four decades generated policy announcements of historically large magnitude, creating variation that is rarely available in conventional samples and that places unusual demands on identification strategies.

A growing literature has responded to this challenge by emphasising that raw high-frequency movements in interest-rate futures conflate two conceptually distinct shocks. The first is a pure monetary policy innovation that tightens or loosens financial conditions. The second is a central bank information shock that conveys the Federal Reserve's assessment of the macroeconomic outlook and moves equity prices in the opposite direction to the policy component. Miranda-Agrippino and Ricco (2021) show that failing to separate these two components substantially biases the estimated responses of financial variables, and Jaroćiński and Karadi (2020) provide a tractable high-frequency identification procedure that achieves this separation without requiring access to internal Federal Reserve forecasts.

Most existing applications of these identification strategies focus on broad equity aggregates such as the S&P 500 or on aggregate macroeconomic variables. The NASDAQ-100, by contrast, concentrates large-capitalisation technology and growth firms whose cash flows are heavily weighted toward the distant future, implying high effective duration and elevated sensitivity to long-horizon discount rate and risk premium revisions. Whether the transmission of pure monetary shocks and information shocks to this high-growth equity segment differs from their transmission to the broad market, particularly during the post-COVID tightening cycle, remains an open empirical question.

This thesis addresses that question. It investigates the transmission of U.S. monetary policy shocks to the NASDAQ-100 over the 2020–2024 period using three complementary empirical exercises unified by the identification discipline of Jaroćiński and Karadi (2020). A high-frequency event study isolates the immediate equity-market response to policy announcements and separates pure monetary shocks from central bank information shocks within narrow intraday windows. A Local Projections-IV framework traces the dynamic propagation of the purified shock over a twenty-four month horizon. A Campbell–Ammer return decomposition attributes the NASDAQ-

100 response to its constituent valuation channels, namely cash-flow news, discount-rate news, and equity risk premium news.

This study contributes to the literature in two main ways. First, it extends informationally robust shock identification, as developed by Miranda-Agrippino and Ricco (2021) and Jaroćiński and Karadi (2020), to a sector-specific high-duration equity index rather than to aggregate macroeconomic variables or broad market indices. Second, it provides evidence on whether the transmission channels documented in earlier literature remain operative during the post-COVID tightening regime, a period of historically large policy adjustments and unusually prominent forward guidance.

The remainder of the thesis proceeds as follows. Section 2 reviews the literature on monetary policy transmission and identification strategies. Section 3 presents the data and empirical methodology. Section 4 reports the event-study and local projections results. Section 5 discusses the findings and robustness analyses. Section 6 concludes.

2 Literature Review

2.1 Introduction

This literature review examines how U.S. monetary policy shocks and broader macroeconomic conditions transmit to equity markets, with a particular focus on the NASDAQ-100 in the post-COVID period. The review is organised around three complementary strands of the empirical and theoretical literature. First, it outlines the key transmission channels through which monetary policy affects equity valuations, thereby establishing the conceptual mechanisms that guide empirical identification. Second, it discusses the specific macroeconomic and policy features of the post-COVID environment, which constitute a structural break in both the conduct of monetary policy and its transmission to financial markets. Third, it reviews the main empirical methodologies used to identify monetary policy shocks, distinguishing between high-frequency event-study approaches and dynamic VAR and SVAR frameworks.

This structure reflects the central challenge of the research question. Monetary policy actions are inherently endogenous to macroeconomic conditions, and equity prices respond simultaneously to policy decisions, macroeconomic news, and changes in expectations. Understanding the transmission of policy to the NASDAQ-100 therefore requires, first, a clear articulation of the channels through which policy affects discount rates, risk premia, credit conditions, and expectations; second, an appreciation of how these channels operate differently in the post-COVID regime characterised by unconventional policy tools, elevated uncertainty, and rapid policy tightening; and third, the use of empirical strategies that can credibly disentangle exogenous policy shocks from contemporaneous information effects.

The NASDAQ-100 provides a particularly informative laboratory for this analysis. Its concentration in growth-oriented technology firms implies high duration, elevated systematic risk, and strong sensitivity to long-horizon discount rates and risk premia. As a result, both monetary policy shocks and macroeconomic surprises are likely to generate amplified and persistent responses relative to broader equity indices. By synthesising insights from the transmission-channel literature, post-COVID macroeconomic analyses, and modern identification strategies, this review motivates the dual empirical approach adopted in the thesis, which combines high-frequency event studies with a local projections instrumental variable framework to capture both the immediate and dynamic effects of monetary policy in the post-pandemic environment.

2.2 Transmission Channels

Understanding how monetary-policy shocks transmit to equity markets is central to the empirical identification of their effects. Existing studies therefore rely on high-frequency event-study designs to isolate the unexpected component of policy decisions and on time-series frameworks to analyze the subsequent dynamics of asset-price adjustment (Bernanke & Kuttner, 2005). For an index such as the NASDAQ-100, which is heavily weighted toward growth-oriented firms with cash flows concentrated in the distant future, these transmission mechanisms are particularly relevant. Rather than operating through a single pathway, the literature emphasizes multiple, interrelated channels through which monetary policy affects equity valuations, most notably changes in discount rates, adjustments in expected risk premia, credit-market conditions, and expectations about the future policy path conveyed through central-bank communication.

The **discount-rate channel** represents the most direct valuation mechanism through which monetary-policy shocks affect equity prices, operating via changes in the risk-free rate used to discount expected future cash flows. Empirical evidence, however, suggests that this channel plays only a limited role in explaining observed stock-market reactions. Using a decomposition based on fed funds futures surprises, Bernanke and Kuttner (2005) show that changes in expected real interest rates account for only a small fraction of the equity response to monetary policy announcements. This finding implies that movements in discount rates alone may not fully explain the magnitude of stock-price adjustments following policy shocks. Complementing this perspective, Thorbecke (2023) estimate monetary-policy betas that measure asset-specific exposure to unexpected policy actions, highlighting systematic cross-sectional differences in how equities load on monetary news, without attributing these effects primarily to changes in real discount rates.

The **risk-premium channel** appears to be a prominent driver. Bernanke and Kuttner (2005) demonstrate that the dominant component of stock-price responses to unanticipated Federal Reserve actions reflects changes in expected excess returns, rather than movements in real interest rates, pointing to time-varying equity risk premia as a key transmission mechanism. Consistent with this interpretation, Laine (2023) show that monetary policy affects implied equity risk premia, including at longer horizons, indicating that policy shocks can alter the pricing of risk embedded in equity valuations. For a high-beta, long-duration index such as the NASDAQ-100, fluctuations in the risk-pricing environment therefore constitute an important source of valuation volatility.

The **credit channel** (or balance-sheet channel) emphasizes that contractionary monetary policy can restrict firms' access to external finance by deteriorating balance-sheet conditions and tightening credit supply. Thorbecke (1997) shows that contractionary monetary policy is associated with declines in stock returns, consistent with a tightening of financial conditions that raises required returns and weakens firms' financial positions. Building on this evidence, Basistha and Kurov (2008) demonstrate that stock-market responses to monetary policy shocks vary systematically over the business cycle. In particular, they document that equity returns react more than twice as strongly to unexpected policy changes during recessions and periods of tight credit conditions, with financially constrained firms exhibiting the greatest sensitivity. These findings provide direct evidence in support of the financial-accelerator mechanism, whereby adverse macroeconomic and credit conditions amplify the transmission of monetary shocks to asset prices. While their analysis is conducted for broad equity markets, the mechanism is especially relevant for technology-oriented firms whose investment and growth prospects depend heavily on external financing.

The **forward-guidance channel** captures the role of central-bank communication in shaping expectations about the future path of monetary policy, particularly when short-term policy rates are constrained. Gürkaynak et al. (2005) decompose monetary policy surprises into a contemporaneous "target" factor associated with the current policy-rate decision and a forward-looking "path" factor reflecting changes in expected future policy. Their results show that forward-guidance shocks exert a strong influence on longer-maturity interest rates and other forward-looking financial variables, while equity prices respond primarily to the target component, with a more limited sensitivity to the path factor. This distinction underscores that forward guidance operates mainly through expectations about future discount rates rather than through immediate equity-market repricing, even though equity valuations are inherently forward-looking.

Although these transmission channels are conceptually distinct, they are empirically intertwined and call for complementary identification strategies. High-frequency event-study approaches are well suited to isolating the immediate response of equity prices to unexpected policy actions (Bernanke & Kuttner, 2005), while state-dependent time-series and regression-based frameworks provide a natural setting for analyzing how monetary shocks propagate over time through credit conditions and macroeconomic states (Basistha & Kurov, 2008). Taken together, this dual empirical approach allows for a coherent analysis of both the short-run market reaction and the longer-run dynamics of monetary-policy transmission.

2.3 Event Study Evidence

Identifying the causal impact of monetary-policy shocks on equity prices is complicated by the endogeneity between policy decisions and the macroeconomic environment. A central contribution of the event-study literature has been to isolate the unexpected component of policy decisions by focusing on narrow announcement windows, thereby mitigating this concern (Bernanke & Kuttner, 2005; Rigobon & Sack, 2006).

Bernanke and Kuttner (2005) provide a seminal contribution by decomposing the equity-market response to federal funds rate surprises into revisions in expected real interest rates, expected dividends, and expected excess returns. Their finding that expected excess return revisions dominate suggests that monetary policy affects equity valuations primarily through risk pricing rather than mechanical discounting of cash flows.

Gürkaynak et al. (2005) demonstrate that a single policy-rate surprise is insufficient to capture the full informational content of FOMC announcements. Extracting two orthogonal factors from federal funds futures and Eurodollar contracts, they show that the path factor, capturing revisions to the expected future policy trajectory, exerts a substantially larger influence on longer-maturity yields than the target factor, implying significant valuation effects for long-duration assets through forward guidance.

Building on this framework, Miranda-Agrippino and Ricco (2021) show that raw high-frequency surprises conflate a pure monetary policy shock with an information shock reflecting the Federal Reserve's private assessment of economic conditions. Projecting the raw surprise onto Greenbook forecasts and retaining the residual attenuates the output and price puzzles commonly observed with unpurified instruments, highlighting that stock-price reactions may partly reflect macroeconomic expectation revisions rather than genuine policy changes. Rigobon and Sack (2006) raise a complementary concern, showing that survey-based surprise measures suffer from errors-in-variables attenuation bias and propose heteroskedasticity-based identification to recover consistent estimates.

The international dimension of U.S. monetary policy transmission has been examined by Ammer et al. (2010), who find that foreign equities respond systematically to U.S. monetary surprises with magnitudes comparable to domestic firms, and that the response is significantly stronger for cyclically sensitive industries, consistent with a demand-driven transmission channel.

Beyond isolated announcement effects, Cieslak et al. (2018) show that a substantial fraction of the annual equity risk premium accrues in windows surrounding FOMC meetings, suggesting that monetary policy information assimilation is a recurrent process. Bauer et al. (2022) further document that elevated policy uncertainty is persistently associated with lower equity returns, indicating an additional channel through which central bank communication shapes asset prices.

Taken together, this evidence supports high-frequency event-study methods as the primary tool for isolating immediate equity-market responses to policy surprises, while underscoring that identification discipline is essential to distinguish genuine monetary innovations from the information component embedded in raw futures movements.

2.4 SVAR / VAR Evidence

The empirical literature on monetary policy transmission to equity markets has evolved through a sequence of increasingly disciplined identification strategies. Early contributions relied on recursive VAR frameworks in which the federal funds rate is ordered first and its orthogonalised innovation interpreted as the monetary policy shock. Using this approach, Thorbecke (1997) shows that an expansionary policy shock raises ex-post stock returns, providing foundational evidence that monetary policy innovations have non-neutral effects on equity prices.

Subsequent advances shifted toward sign-restriction and external-instrument approaches to address the limitations of recursive ordering. Wolf (2020) demonstrates that weak sign restrictions can admit masquerading shocks that satisfy the imposed sign conditions while failing to represent the true monetary impulse, leading to attenuated impulse responses. Building directly on this concern, Jaroćiński and Karadi (2020) propose a high-frequency classification procedure that distinguishes pure monetary policy shocks from central bank information shocks on the basis of the co-movement between interest rate surprises and equity price responses within narrow FOMC announcement windows. This procedure provides a tractable identification strategy that imposes economically disciplined restrictions without requiring access to internal Federal Reserve forecasts.

The most influential methodological benchmark is provided by Miranda-Agrippino and Ricco (2021). They show that the conventional high-frequency instrument, namely raw intraday movements in federal funds futures, conflates two conceptually distinct shocks: a pure monetary policy shock that changes the policy stance, and an information shock that conveys the Federal Reserve's private assessment of macroeconomic conditions. To obtain an informationally robust instrument, they project the raw surprise onto Greenbook forecasts of output, inflation, and unemployment and retain the residual. Once embedded in a Bayesian Proxy-SVAR, this purified shock eliminates the output and price puzzles commonly observed with raw surprises, producing impulse responses consistent with standard macroeconomic theory. Their contribution establishes the methodological benchmark that the present thesis operationalises for equity-market applications.

Taken together, this progression from recursive ordering to informationally robust external instruments underscores the central role of identification discipline for credible inference about monetary transmission. Each refinement reduces the risk of conflating genuine policy actions with the central bank's concurrent assessment of economic conditions, the distinction that motivates the empirical strategy of the present thesis.

2.5 Summary and Research Gap

The literature documents that U.S. monetary policy influences equity markets through several interrelated channels, including discount rate adjustments, revisions in equity risk premia, credit condition effects, and forward guidance. High frequency event study designs isolate the immediate repricing of financial assets around Federal Open Market Committee announcements, while VAR and SVAR frameworks trace the dynamic propagation of monetary shocks through macroeconomic and financial variables. More recent proxy SVAR approaches employ external high frequency instruments to strengthen identification by separating pure policy innovations from contemporaneous information effects.

Miranda-Agrippino and Ricco (2021) show that raw intraday movements in federal funds futures combine two distinct components. The first is a pure monetary policy shock that changes the stance of policy. The second is an information shock that reflects the Federal Reserve's internal assessment of macroeconomic conditions. By projecting the raw surprise on Greenbook forecasts and retaining the residual, they construct an informationally robust external instrument. When this purified shock is used within a Bayesian proxy SVAR, the output and price puzzles disappear and the impulse responses become consistent with standard New Keynesian predictions. Their contribution establishes a methodological benchmark for identifying monetary policy shocks at the aggregate macroeconomic level.

Two related dimensions motivate further investigation. First, most empirical applications of informationally robust shocks focus on aggregate macroeconomic variables or broad equity indices. Such aggregates provide a comprehensive view of overall market dynamics but do not allow for an assessment of whether monetary transmission differs across equity segments with distinct valuation characteristics. The NASDAQ-100 is composed predominantly of large capitalization firms in technology and growth oriented sectors. Valuation theory suggests that firms whose prices depend heavily on expectations about future profitability may exhibit greater sensitivity to discount rate and risk premium revisions. Examining the response of this index therefore allows for a more targeted evaluation of how purified monetary policy shocks transmit to a high growth equity segment.

Second, the post-COVID monetary environment differs from the historical samples commonly used in earlier studies. It combines an extended period at the effective lower bound with extensive forward guidance and asset purchases, followed by a rapid tightening cycle. In such a context, high frequency futures surprises may embed sizeable revisions in policy expectations alongside contemporaneous information about the economic outlook. Evaluating informationally robust monetary policy shocks within this regime provides evidence on whether identification discipline remains equally important under conditions of pronounced forward guidance and rapid rate adjustments.

Addressing these issues requires an integrated empirical framework. The present thesis therefore pursues three objectives. First, it constructs informationally robust monetary policy shocks for the post-COVID period by applying the sign-restriction classification of Jaroćiński and Karadi (2020) to high-frequency futures data. This approach operationalises the conceptual distinction between pure monetary policy shocks and central bank information shocks established by Miranda-Agrippino and Ricco (2021), while accommodating the five-year publication lag that renders Greenbook forecast data unavailable for the period under study. Second, it decomposes NASDAQ-100 excess returns into cash flow news, real rate news, and risk premium news using the Campbell and Ammer framework. Third, it embeds the identified shock within a local projections instrumental variable framework to trace the medium-term propagation of monetary policy innovations through macroeconomic variables and the NASDAQ-100.

By extending informationally disciplined identification to a sector specific equity index and to a recent monetary regime characterized by substantial forward guidance revisions and rapid policy adjustments, the analysis complements existing aggregate evidence and contributes additional insight into the heterogeneity of monetary transmission across equity markets.

2.6 Research Hypotheses

The literature reviewed above highlights three principal channels through which monetary policy affects equity prices: revisions in discount rates, changes in expected future cash flows, and adjustments in required risk premia. High-frequency identification strategies allow researchers to isolate the unexpected component of policy announcements, while structurally disciplined frameworks trace the dynamic propagation of these shocks over time.

Because the NASDAQ-100 is predominantly composed of growth-oriented firms whose valuations are sensitive to changes in discount rates and risk premia, monetary policy innovations are expected to generate measurable valuation adjustments both at high frequency and over subsequent periods.

Based on these considerations, the following hypotheses are formulated:

— **H1: Immediate Reaction.** Under the present value framework, unexpected monetary policy shocks induce immediate adjustments in equity prices through revisions in discount rates and risk premia (Bernanke & Kuttner, 2005). Accordingly, unexpected U.S. monetary policy shocks generate statistically significant abnormal returns in the NASDAQ-100 within narrow announcement windows.

— **H2: Risk-Premium Channel.** Empirical evidence suggests that the equity market response to monetary policy surprises is driven predominantly by changes in expected excess returns rather than by contemporaneous revisions of expected cash flows (Bernanke & Kuttner, 2005; Campbell & Ammer, 1993). Therefore, the short-run response of the NASDAQ-100 to monetary policy surprises is expected to be driven primarily by revisions in the equity risk premium.

— **H3: Forward-Guidance Effects.** Forward-guidance announcements alter expectations about the future path of policy rates and thus affect long-horizon discount factors (Gürkaynak et al., 2005). Given the longer effective duration of growth-oriented firms, path surprises are expected to exert a statistically significant and economically distinct effect on NASDAQ-100 returns relative to contemporaneous target-rate surprises.

— **H4: Dynamic Propagation.** Structural evidence indicates that monetary policy shocks propagate over time through macroeconomic and financial channels (Miranda-Agrippino

& Ricco, 2021; Thorbecke, 1997). Monetary policy shocks identified using a structurally disciplined local projections framework are therefore expected to influence NASDAQ-100 returns over several months, exhibiting a dynamic adjustment pattern distinct from the immediate announcement effect.

— **H5: Pure Monetary versus Information Shocks.** When high-frequency surprises are decomposed into pure monetary policy shocks and information shocks (Jarociński & Karadi, 2020; Miranda-Agrippino & Ricco, 2021), pure contractionary monetary innovations are expected to reduce NASDAQ-100 returns through higher discount rates and risk premia. In contrast, information shocks reflecting improved macroeconomic outlooks may partially offset this effect through revisions in expected cash flows or perceived risk.

3 Data and Empirical Methodology

3.1 Overview of the Empirical Strategy

The empirical strategy is organised around three sequential and mutually reinforcing exercises. First, a high-frequency event-study design estimates the immediate NASDAQ-100 response within a narrow window around each FOMC announcement, following Bernanke and Kuttner (2005) and Kuttner (2001). Second, a Local Projections-IV framework (Jordà, 2005; Stock & Watson, 2018) traces the dynamic impulse response over a twenty-four month horizon using an external instrument that separates pure monetary policy shocks from the central bank information component embedded in raw futures surprises (Jaroćiński & Karadi, 2020; Miranda-Agrippino & Ricco, 2021). Third, the Campbell–Ammer decomposition (Campbell, 1991; Campbell & Ammer, 1993) attributes the NASDAQ-100 excess return to cash-flow news, discount-rate news, and equity risk premium news, and relates each component to the identified shocks.

Table 1 summarises the three exercises, their respective methodologies, estimation samples, and the hypotheses to which each contributes.

Table 1 – Overview of the Empirical Strategy

Exercise	**Estimator**	**Sample**	**Frequency**	**Hypotheses**
Event Study	OLS, HC3 SE	2020–2024 ($N = 40$ events)	Intraday (±30 min)	H1, H3, H5
LP-IV	Jordà (2005)	1994M02–2024M12 ($T = 371$ months)	Monthly	H4, H5
Return Decomposition	Campbell and Ammer (1993) VAR(1)	2001M05–2024M12 ($T = 267$ months)	Monthly	H2

Notes: HC3 denotes the heteroskedasticity-consistent covariance matrix estimator of MacKinnon and White (1985). LP-IV refers to the local projections instrumental variables estimator. The event-study sample covers the post-COVID monetary regime, encompassing both the effective lower bound period and the subsequent tightening cycle. The Campbell–Ammer sample begins in 2001M05 after first-differencing the ten-year nominal yield. Hypotheses are as defined in Section 2.6.

The three exercises are complementary by design. The event study captures the immediate repricing at announcement frequency but is silent on medium-term propagation. The LP-IV framework traces the full dynamic response over twenty-four months while preserving identification discipline. The Campbell–Ammer decomposition then attributes the total return response to its constituent valuation channels. Together, they provide a coherent account of both short-run and medium-run monetary policy transmission to a high-duration growth equity index.

3.2 Data

High-Frequency Event-Study Data

The event-study analysis is conducted on a sample of $N = 40$ scheduled FOMC announcement days over the period 2020–2024.[1] For each event, high-frequency data are obtained from Bloomberg at one-minute intervals.

The *monetary policy surprise* is constructed from federal-funds futures contracts following Kuttner (2001) and Bernanke and Kuttner (2005). Because federal-funds futures are quoted as prices equal to 100 minus the expected average federal funds rate, changes in futures prices are inversely related to changes in the expected policy rate: a positive price change implies a downward revision in the expected rate, and vice versa. Surprise measures are accordingly defined as changes in the *implied rate*, so that a positive value denotes an unexpectedly restrictive policy outcome (Kuttner, 2001).

Two measures are constructed. The *current-meeting surprise*, s_t^{FF1}, captures the unexpected change in the policy rate decision at the current meeting and is defined as the change in the implied rate of the first nearby federal-funds futures contract (FF1) within a ±30-minute window centred on the official announcement time τ:

$$s_t^{FF1} \;=\; -(FF1_{t,\,\tau+30} \;-\; FF1_{t,\,\tau-30})\,, \tag{1}$$

where subscripts denote minutes relative to τ and the negative sign converts the price change into an implied rate change. The *four-meeting-ahead surprise*, s_t^{FF4}, is constructed analogously using the implied rate of the fourth nearby federal-funds futures contract (FF4):

$$s_t^{FF4} \;=\; -(FF4_{t,\,\tau+30} \;-\; FF4_{t,\,\tau-30})\,, \tag{2}$$

and serves as the baseline measure of the unexpected component of the policy announcement, as it captures both the current decision and its implications for the near-term policy path (Bernanke & Kuttner, 2005). A *path surprise* is then defined as the component of s_t^{FF4} that is orthogonal to the current-meeting decision:

$$s_t^{path} \;=\; s_t^{FF4} \;-\; s_t^{FF1}, \tag{3}$$

following the approximation of Gürkaynak et al. (2005).[2] All surprise measures are expressed in percentage points of the implied policy rate.

The *NASDAQ-100 return* is measured as the log price change of the front-month NASDAQ-

1. One additional meeting — the emergency inter-session decision of 15 March 2020 — is excluded due to the absence of a standard pre-announcement window, as the decision was released outside regular trading hours without prior scheduling.

2. Gürkaynak et al. (2005) extract two orthogonal factors from a panel of five futures contracts using principal component analysis. The approximation $s_t^{path} = s_t^{FF4} - s_t^{FF1}$ is a widely used simplification (Jaroćiński & Karadi, 2020; Nakamura & Steinsson, 2018) that does not require Eurodollar contract data and closely replicates the path factor of the original decomposition.

100 E-mini futures contract (NQ) within the same ±30-minute window:

$$r_t^{NQ} = \ln\left(\frac{NQ_{t,\tau+30}}{NQ_{t,\tau-30}}\right) \times 100. \tag{4}$$

A ±30-minute window is standard in the high-frequency identification literature and balances the need to capture the immediate announcement effect against the risk of contamination from unrelated macroeconomic news (Bernanke & Kuttner, 2005; Gürkaynak et al., 2005). The S&P 500 E-mini futures return, r_t^{SP500}, is constructed identically and is used solely for the shock classification procedure described in Section 3.2. The final event-study dataset comprises $N = 40$ observations with no missing values.

Table 2 – Descriptive Statistics — Event-Study Sample (2020–2024)

Variable	Mean	Std. Dev.	Min	Max	Obs.
NQ return r_t^{NQ} (%)	0.04	0.87	−2.13	2.05	40
FF4 surprise s_t^{FF4} (pp)	0.00	0.08	−0.25	0.22	40
FF1 surprise s_t^{FF1} (pp)	0.00	0.03	−0.14	0.08	40
Path surprise s_t^{path} (pp)	0.00	0.07	−0.21	0.20	40

Notes: The sample covers 40 scheduled FOMC announcement days, 2020–2024. All variables are measured within a ±30-minute window around each announcement. pp = percentage points of the implied policy rate. The path surprise is defined as $s_t^{path} = s_t^{FF4} - s_t^{FF1}$.

Monthly Macroeconomic Data

The LP-IV estimation uses a monthly dataset spanning February 1994 to December 2024 ($T = 371$ observations), sourced from the Federal Reserve Economic Data (FRED) database and Bloomberg. The system comprises seven variables, selected to capture the main transmission channels reviewed in Section 2. All transformations are designed to ensure stationarity, as verified by augmented Dickey-Fuller tests applied to each series.

Real activity and prices. The log-difference of the Federal Reserve's index of industrial production, $\Delta \log \mathrm{IP}_t = \log \mathrm{IP}_t - \log \mathrm{IP}_{t-1}$, measures monthly output growth. The month-on-month log-difference of the Consumer Price Index, $\Delta \log \mathrm{CPI}_t = \log \mathrm{CPI}_t - \log \mathrm{CPI}_{t-1}$, measures inflation. Both series are included in first differences to ensure stationarity.

Monetary policy. The effective federal funds rate, FFR_t, is included in levels. Although the series exhibits high persistence, inclusion in levels is standard in monthly LP and VAR frameworks for monetary policy analysis, as differencing would remove the low-frequency variation that is central to the identification of policy shocks (Gertler & Karadi, 2015; Miranda-Agrippino & Ricco, 2021).

Equity market. The log-return of the NASDAQ-100, $\Delta \log \mathrm{NDX}_t = \log \mathrm{NDX}_t - \log \mathrm{NDX}_{t-1}$, is the variable of primary interest.

Financial conditions. The first difference of the ten-year U.S. Treasury constant-maturity yield, $\Delta y_t^{10Y} = y_t^{10Y} - y_{t-1}^{10Y}$, proxies for changes in long-term discount rates. The first difference of the BBB-rated corporate credit spread over the ten-year Treasury, $\Delta \mathrm{CS}_t = \mathrm{CS}_t - \mathrm{CS}_{t-1}$, captures changes in credit-market tightness consistent with the financial accelerator mechanism (Basistha & Kurov, 2008). The first difference of the CBOE Volatility Index, $\Delta \mathrm{VIX}_t = \mathrm{VIX}_t - \mathrm{VIX}_{t-1}$, measures changes in equity market uncertainty (Bekaert et al., 2013). All series are end-of-month aligned. Table 3 provides a complete summary of sources, series identifiers, and transformations.

Table 3 – Monthly Macroeconomic Data — Sources and Transformations

Variable	**Notation**	**Series / Ticker**	**Source**	**Transformation**
Industrial production index	IP_t	INDPRO	FRED	Log-difference $\Delta \log \mathrm{IP}_t$
Consumer price index	CPI_t	CPIAUCSL	FRED	Log-difference $\Delta \log \mathrm{CPI}_t$
Federal funds rate	FFR_t	FEDFUNDS	FRED	Level
NASDAQ-100 index	NDX_t	NDX Index	Bloomberg	Log-difference $\Delta \log \mathrm{NDX}_t$
10-year Treasury yield	y_t^{10Y}	DGS10	FRED	First difference Δy_t^{10Y}
BBB credit spread	CS_t	BAMLC0A4CBBB	FRED	First difference $\Delta \mathrm{CS}_t$
CBOE VIX	VIX_t	VIXCLS	FRED	First difference $\Delta \mathrm{VIX}_t$

Notes: Sample period: February 1994 to December 2024 ($T = 371$ monthly observations). All series are aligned to end-of-month dates. FRED denotes the Federal Reserve Economic Data database. Stationarity of all transformed series is confirmed by augmented Dickey-Fuller tests at the 5% significance level.

Monetary Policy Shock Classification

A central identification challenge in this literature is that raw high-frequency movements in federal-funds futures conflate two conceptually distinct shocks: a *pure monetary policy (MP) shock* that changes the stance of policy, and a *central bank information (CBI) shock* that conveys the Federal Reserve's private assessment of macroeconomic conditions (Jaroćiński & Karadi, 2020; Miranda-Agrippino & Ricco, 2021). As demonstrated by Miranda-Agrippino and Ricco (2021), failing to separate these two components can substantially bias the estimated responses of financial variables, because the two shocks exert *opposite* effects on equity prices: a contractionary MP shock reduces equity valuations through higher discount rates and risk premia, whereas a positive CBI shock raises them through upward revisions in expected future cash flows.

The present study separates the two shock types using the *poor-man's sign restriction* of Jaroćiński and Karadi (2020). This procedure classifies each FOMC meeting based on the contemporaneous co-movement between the federal-funds futures surprise and the S&P 500 return within the announcement window. If the two variables move in *opposite* directions — a positive rate surprise accompanied by a negative equity return — the announcement is classified as a pure MP shock, consistent with the canonical transmission of a restrictive policy action. If they move in the *same* direction — rates and equities rising together — the announcement is classified as a CBI shock, consistent with the market interpreting the announcement as conveying positive news about the economic outlook. Formally:

$$\text{Type}_t = \begin{cases} \text{MP} & \text{if} \quad \text{sgn}\left(s_t^{FF4}\right) \neq \text{sgn}\left(r_t^{SP500}\right), \\ \text{CBI} & \text{if} \quad \text{sgn}\left(s_t^{FF4}\right) = \text{sgn}\left(r_t^{SP500}\right). \end{cases} \tag{5}$$

The exact purification approach of Miranda-Agrippino and Ricco (2021) projects the raw high-frequency surprise onto the Federal Reserve's *Greenbook* forecasts of output, inflation, and unemployment to isolate the information component from the raw surprise. However, Greenbook data are released with a five-year publication lag and are therefore unavailable for the post-2020 period that constitutes the primary focus of the event-study analysis. In response to this objective data constraint, the identification strategy relies on the Jaroćiński and Karadi (2020) sign restriction, which constitutes a well-established and widely applied alternative that does not require access to the Federal Reserve's internal forecasts. The sign-based classification provides a practical approximation that is broadly consistent with the distinction between pure policy shocks and information shocks emphasised in the literature (Jaroćiński & Karadi, 2020; Miranda-Agrippino & Ricco, 2021), even if it cannot fully replicate the precision of a Greenbook-based purification.

The monthly shock series used in the LP-IV exercise are taken from the Jaroćiński and Karadi (2020) replication dataset and extended to December 2024. For the post-sample period (January 2021 to December 2024), the series are extended by applying the same sign-restriction classification of equation (5) to the high-frequency futures surprises and equity returns collected for the event-study exercise. For the post-sample extension period considered here, scheduled FOMC meetings occur at most once per calendar month, so each event can be mapped to a unique calendar month. The monthly shock value is set equal to the futures-based surprise s_t^{FF4} for MP-classified events and to zero for non-event months; CBI-classified events are similarly assigned their s_t^{FF4} value in the CBI series and zero in the MP series. This assignment procedure ensures that the monthly series are directly comparable to the original Jaroćiński and Karadi (2020) replication dataset. Over the full sample ($T = 371$ months), 167 months contain a non-zero MP shock and 86 months contain a non-zero CBI shock. The sample correlation between the two monthly series is 0.015, confirming near-orthogonality of the two shock types.

Campbell-Ammer State Variables

The return decomposition exercise uses a monthly dataset spanning March 2001 to December 2024 ($T = 268$ observations). The Campbell-Ammer framework, described in detail in Section 3.5, decomposes unexpected excess equity returns into revisions in expected future cash flows, real interest rates, and equity risk premia. The state vector required to implement this decomposition comprises five variables selected to capture the predictive content of both future cash flows and future discount rates, following the specification of Campbell and Ammer (1993).

The purpose of the state vector is to capture the information set that market participants use to forecast future excess returns, future real interest rates, and future cash flows: these forecasts are precisely what the Campbell-Ammer decomposition requires in order to attribute unexpected equity returns to their respective news components.

The *NASDAQ-100 monthly excess return* is defined as:

$$r_t^e = r_t^{NQ,\,monthly} - r_t^f, \tag{6}$$

where $r_t^{NQ,\,monthly}$ is the log return of the NASDAQ-100 index over month t and $r_t^f = y_t^{3M}/12$ is the monthly risk-free rate, proxied by the three-month U.S. Treasury bill yield divided by twelve. The remaining four state variables are: the NASDAQ-100 *dividend yield*, dy_t, which captures expectations about long-horizon cash flows (Campbell & Ammer, 1993; Fama, 1990); the log *price-to-earnings ratio*, $\log(\mathrm{P/E})_t$, which captures current equity market valuation levels; the *term spread*, defined as the ten-year minus the three-month U.S. Treasury yield, TS_t, which predicts future real economic conditions and discount rates; and the *ten-year U.S. Treasury yield*, y_t^{10Y}, which proxies for the level of long-term nominal interest rates. The sample begins in March 2001 due to data availability for the NASDAQ-100 dividend yield series.

Data-processing pipeline. All high-frequency series are aligned to FOMC announcement timestamps, with each observation assigned to the ±30-minute window centred on the official announcement time. All monthly series are aligned to end-of-month dates, and missing observations are addressed through backward fill for yield series where a single trading-day gap exists at month end. All transformed variables — including log-differenced output, inflation, and equity returns, as well as first-differenced yields, spreads, and volatility — are tested for stationarity using augmented Dickey-Fuller tests prior to estimation; all series included in the LP-IV and Campbell-Ammer systems are found to be stationary at the 5 per cent significance level. This pipeline ensures consistency of temporal alignment across the three empirical exercises and facilitates direct comparability of results.

3.3 High-Frequency Event Study

Identification Strategy

The identifying assumption underlying the event-study design is that, within a narrow window of ±30 minutes around each FOMC announcement, all systematic variation in the NASDAQ-100 return is attributable to the monetary policy surprise and not to concurrent macroeconomic news. This assumption is supported by the extensive event-study literature, which has established that ±30-minute windows are sufficiently narrow to eliminate contamination from other scheduled macroeconomic releases while providing adequate time for market prices to incorporate the informational content of the policy decision (Bernanke & Kuttner, 2005; Gürkaynak et al., 2005; Kuttner, 2001). Under this assumption, the ordinary least squares (OLS) estimator applied to announcement-day observations yields a consistent estimate of the causal effect of monetary policy surprises on equity returns.

A potential concern, noted by Rigobon and Sack (2006), is that survey-based or futures-based surprise measures may contain classical measurement error, which would attenuate OLS estimates toward zero. The use of liquid federal-funds futures contracts within a narrow intraday window minimises this concern, as the futures price is continuously updated by informed market participants and is unlikely to embed systematic measurement error over a 60-minute period. A related concern, discussed extensively by Miranda-Agrippino and Ricco (2021) and Jaroćiński and Karadi (2020), is that the raw surprise s_t^{FF4} may conflate a genuine policy innovation with a central bank information component. The implications of this conflation for the estimated event-study coefficients are examined directly in Section 3.3, where the two shock types are separated following the classification of Section 3.2.

Baseline Specification (H1)

The baseline specification for testing Hypothesis H1 regresses the NASDAQ-100 intraday return on the FF4 futures surprise:

$$r_t^{NQ} \;=\; \alpha \;+\; \beta \cdot s_t^{FF4} \;+\; \varepsilon_t, \qquad t = 1, \ldots, N, \tag{7}$$

where r_t^{NQ} is the NASDAQ-100 intraday log return as defined in equation (4), s_t^{FF4} is the FF4 monetary policy surprise as defined in equation (2), α is a constant, and ε_t is a mean-zero disturbance term. The coefficient of interest, β, measures the percentage-point change in the NASDAQ-100 associated with a one-percentage-point unexpected increase in the four-meeting-ahead federal funds rate. Under Hypothesis H1, β is expected to be negative and statistically significant, reflecting an immediate contractionary effect of unexpected monetary tightening on equity valuations.

All specifications are estimated by OLS. Standard errors are computed using the heteroskedasticity-consistent HC3 estimator, introduced by MacKinnon and White (1985) as the leverage-corrected variant of the White (1980) sandwich estimator. HC3 applies a squared leverage correction to each squared residual and has superior finite-sample properties relative to the HC1 and HC2 variants, particularly in the presence of influential observations (Herbst & Johannsen, 2021). Given the small sample of $N = 40$ observations, it is the preferred estimator throughout the event-study analysis.

Target-Rate versus Forward-Guidance Decomposition (H3)

To test Hypothesis H3, the single surprise s_t^{FF4} in equation (7) is replaced by its two constituent components — a contemporaneous target-rate surprise and a forward-guidance (path) surprise — following the two-factor structure of Gürkaynak et al. (2005):

$$r_t^{NQ} \;=\; \alpha \;+\; \beta_1 \cdot s_t^{FF1} \;+\; \beta_2 \cdot s_t^{path} \;+\; \varepsilon_t, \tag{8}$$

where s_t^{FF1} is the current-meeting surprise from equation (1) and $s_t^{path} = s_t^{FF4} - s_t^{FF1}$ is the path surprise from equation (3). The coefficient β_1 measures the sensitivity of the NASDAQ-100 to the contemporaneous target-rate decision, while β_2 measures its sensitivity to forward-guidance revisions about the future policy path.

Hypothesis H3 predicts that β_2 should be statistically significant and, in absolute magnitude, potentially larger than β_1. This prediction follows from the valuation structure of growth-oriented technology firms, whose cash flows are concentrated at long horizons. Because such firms have high effective duration, their equity prices are more sensitive to revisions in long-horizon discount rates than to contemporaneous short-rate adjustments (Gürkaynak et al., 2005). In the post-COVID tightening cycle, in which the Federal Reserve communicated an extended sequence of rate increases, the path component of FOMC announcements is expected to have been particularly informative for long-duration assets such as the NASDAQ-100.

Pure Monetary versus Information Shocks (H5)

To test Hypothesis H5 at high frequency, FOMC meetings are partitioned into pure MP events and CBI events using the classification of equation (5). The average NASDAQ-100 return is computed separately for each group, and the null hypothesis of equal means is assessed using a two-sample t-test on the group means. In addition, the difference in means is assessed within a regression framework — regressing r_t^{NQ} on a binary indicator equal to one for MP events and zero for CBI events — using HC3 robust standard errors, which constitutes the primary basis for inference given the small and unbalanced group sizes. Hypothesis H5 predicts that the mean return on MP days, $\bar{r}^{MP}$, will be significantly negative, and the mean return on CBI days, $\bar{r}^{CBI}$, will be positive, with a statistically significant difference between the two:

$$H_0: \ \bar{r}^{MP} = \bar{r}^{CBI} \qquad \text{against} \qquad H_1: \ \bar{r}^{MP} < \bar{r}^{CBI}. \tag{9}$$

In addition, to quantify the magnitude of the information bias in the raw FF4 surprise, the baseline regression (7) is re-estimated separately using the raw surprise s_t^{FF4} and a purified shock constructed by zeroing out CBI events (setting $s_t^{FF4} = 0$ on CBI days). The difference between the two estimated coefficients provides a direct measure of the attenuation bias introduced by the information component, and constitutes a high-frequency analogue of the purification exercise conducted at monthly frequency in Section 3.4.

3.4 Local Projections-Instrumental Variables

Choice of LP-IV over Proxy-SVAR

The standard approach in the monetary policy transmission literature for estimating dynamic causal effects is the Proxy Structural Vector Autoregression (Proxy-SVAR) of Mertens and Ravn (2013), in which an external instrument is embedded within a structural VAR framework to identify a single structural shock. However, in the present application, this approach faces a dimensionality constraint that renders it impractical.

A Proxy-SVAR with $K = 7$ variables estimated at the monthly frequency conventionally requires $p = 12$ lags to adequately capture the autocorrelation structure of the data, as recommended by Miranda-Agrippino and Ricco (2021) for similar systems. The number of freely estimated parameters in the VAR companion matrix is then $K^2 \times p = 7^2 \times 12 = 588$, for a sample of only $T = 371$ monthly observations. This parameter-to-observation ratio of approximately 1.6 is likely to produce poorly conditioned coefficient matrices, unstable bootstrapped impulse responses, and unreliable inference at medium horizons.

The Local Projections (LP) framework of Jordà (2005) provides a robust and well-established alternative. Rather than estimating a single VAR model and then inverting it to recover impulse responses at all horizons simultaneously, the LP approach estimates a separate reduced-form regression for each horizon h of interest. This has three important advantages in the present context. First, LP avoids the parameter accumulation inherent in VAR inversion: each horizon-specific regression involves only $K \times L$ parameters, where L is the number of control lags, regardless of how many horizons are examined. Second, LP estimates are more robust to lag misspecification than VAR estimates: Plagborg-Møller and Wolf (2021) establish the asymptotic equivalence of LP and VAR impulse responses under correct specification, and demonstrate that LP is more robust when the lag order is misspecified. Third, the LP framework accommodates the introduction of instrumental variables in a straightforward manner, yielding the LP-IV estimator of Stock and Watson (2018), which recovers causal impulse responses without requiring full identification of the structural VAR. Notably, Miranda-Agrippino and Ricco (2021) themselves employ LP-IV as a robustness check to their Proxy-SVAR results in their Figure 12, providing direct methodological precedent for this choice.

LP-IV Specification

The LP-IV estimator is obtained by instrumenting the endogenous shock with the external MP instrument z_t in a sequence of horizon-specific regressions. For each horizon $h = 0, 1, \ldots, 24$ and each variable k in the system, the specification is:

$$\sum_{j=0}^{h} Y_{t+j,\,k} \;=\; \alpha_{h,k} \;+\; \beta_{h,k} \cdot z_t \;+\; \sum_{\ell=1}^{L} \boldsymbol{\gamma}'_{\ell,k} \mathbf{Y}_{t-\ell} \;+\; \varepsilon_{t,\,h,\,k}, \tag{10}$$

where the left-hand side, $\sum_{j=0}^{h} Y_{t+j,\,k}$, is the *cumulative* response of variable k from period t to period $t+h$; z_t is the external instrument, equal to the monthly MP shock series $\mathrm{MP}_{pm,t}$ as defined in Section 3.2; $\mathbf{Y}_{t-\ell}$ is the $(K \times 1)$ vector of all system variables at lag ℓ, included as controls to absorb any predictable variation in $Y_{t+j,k}$ that is not attributable to the shock; $\boldsymbol{\gamma}_{\ell,k}$ is the corresponding $(K \times 1)$ vector of control coefficients; and $\varepsilon_{t,\,h,\,k}$ is a mean-zero disturbance term that is allowed to be heteroskedastic.

The coefficient $\beta_{h,k}$ is the object of interest at each horizon: it measures the average cumulative response of variable k over h months following a unit innovation in z_t, holding the history of all other variables fixed. Plotting $\hat{\beta}_{h,k}$ against h for $h = 0, 1, \ldots, 24$ yields the estimated impulse response function (IRF) of variable k to the MP shock.

The system variables are $\mathbf{Y}_t = (\Delta \log \mathrm{IP}_t,\ \Delta \log \mathrm{CPI}_t,\ \mathrm{FFR}_t,\ \Delta \log \mathrm{NDX}_t,\ \Delta y_t^{10Y},\ \Delta \mathrm{CS}_t,\ \Delta \mathrm{VIX}_t)'$, as described in Section 3.2. The lag order is set to $L = 4$, following the standard recommendation of Jordà (2005) for monthly LP specifications. This choice is supported by the Bayesian Information Criterion (BIC) applied to the system, and is robust to the use of $L \in \{2, 6, 8\}$ lags as verified in the robustness analysis of Section 5.4.

Normalisation

The raw LP-IV coefficient $\hat{\beta}_{h,k}$ measures the response of variable k to a one-unit change in the instrument z_t. However, the unit of z_t is the JK poor-man's shock series, which is not directly interpretable in terms of the federal funds rate. To facilitate economic interpretation and comparability with the existing literature, impulse responses are normalised to correspond to a one-percentage-point increase in the federal funds rate at impact, following the convention of Gertler and Karadi (2015) and Miranda-Agrippino and Ricco (2021).

Formally, the normalised impulse response of variable k at horizon h is defined as:

$$\widehat{\mathrm{IRF}}_{h,k} \;=\; \frac{\hat{\beta}_{h,k}}{\hat{\beta}_{0,\,\mathrm{FFR}}}, \tag{11}$$

where $\hat{\beta}_{0,\,\mathrm{FFR}}$ is the estimated coefficient from equation (10) with $k = \mathrm{FFR}$ and $h = 0$, that is, the impact response of the federal funds rate to one unit of the instrument. Dividing by $\hat{\beta}_{0,\,\mathrm{FFR}}$ rescales all responses so that the federal funds rate increases by exactly one percentage point on impact. In the present estimation, $\hat{\beta}_{0,\,\mathrm{FFR}} = 1.09$, meaning that one unit of the MP instrument raises the federal funds rate by 1.09 percentage points on impact; all other impulse responses are divided by this scalar. This normalisation is purely a rescaling and does not affect the statistical significance of the estimated responses.

Standard Errors

Standard errors are computed separately at each horizon h using the HC3 heteroskedasticity-consistent estimator of MacKinnon and White (1985). The use of HC3 rather than Newey-West HAC standard errors is motivated by the structure of the LP residuals. At horizon h, the dependent variable $\sum_{j=0}^{h} Y_{t+j,k}$ is a cumulative sum, which by construction induces moving-average serial correlation of order h in $\varepsilon_{t,h,k}$. However, Herbst and Johannsen (2021) show that, in LP regressions of this type, Newey-West corrections tend to over-smooth the variance-covariance matrix at short horizons and under-smooth it at long horizons. HC3 is preferred in the present application because it avoids the need to select a bandwidth parameter and provides a finite-sample correction for heteroskedasticity, which is particularly relevant given the moderate sample size and the horizon-by-horizon estimation strategy. Confidence intervals are constructed as $\widehat{\mathrm{IRF}}_{h,k} \pm 1.96 \times \widehat{\mathrm{SE}}_{h,k}$, corresponding to asymptotic 95 per cent bands. As is standard in LP applications, the width of these confidence intervals increases with h, reflecting the growing uncertainty about longer-horizon responses; statistically precise inference is therefore primarily concentrated at horizons $h = 0$ to $h = 3$.

Instrument Validity

Identification in the LP-IV framework rests on two standard conditions that the external instrument z_t must satisfy: *relevance*, which requires that z_t is sufficiently correlated with the endogenous variable of interest, and *exogeneity*, which requires that z_t affects the outcome variables only through the endogenous channel and not directly.

Relevance. The relevance condition is assessed via the first-stage F-statistic from a regression of z_t on all system variables at impact, after partialling out the $L = 4$ lag controls using the Frisch-Waugh-Lovell (FWL) theorem. The FWL approach correctly accounts for the projection of z_t onto the control space and yields an F-statistic of 30.25, well above the conventional weak-instrument threshold of 10 proposed by Stock and Yogo (2005). This indicates that the MP shock series is a strong predictor of the federal funds rate innovation, confirming its suitability as an external instrument. For comparison, a Newey-West HAC-corrected F-statistic of 8.96 is also reported; this figure falls slightly below the threshold of 10 due to the autocorrelation correction, but the FWL statistic, which does not require a bandwidth choice, is the preferred diagnostic. The relevance condition is considered satisfied on the basis of the FWL statistic. Miranda-Agrippino and Ricco (2021) report a comparable first-stage F-statistic of approximately 15 for their Greenbook-purified instrument, indicating that the JK poor-man's series exhibits comparable or stronger predictive power for the policy rate.

Exogeneity. The exogeneity condition requires that z_t is not predictable from the history of the macroeconomic system, that is, that it contains a genuinely unexpected component. This is assessed by regressing z_t on $L = 4$ lags of all seven system variables and testing the joint significance of the lagged regressors via an F-test. The resulting statistic is $F = 1.62$ ($p = 0.119$), failing to reject the null hypothesis of unpredictability at conventional significance levels. This result indicates that the MP shock series cannot be predicted from the prior history of output, inflation, interest rates, equity returns, or financial conditions, which is consistent with the interpretation that the series captures a genuinely exogenous policy innovation rather than a systematic response to macroeconomic conditions. An additional plausibility check confirms near-orthogonality between the MP and CBI series: the sample correlation is 0.015, which is statistically indistinguishable from zero.

3.5 Campbell-Ammer Return Decomposition

Conceptual Framework

The Campbell-Ammer decomposition provides a variance-accounting framework that attributes unexpected equity returns to three economically distinct sources of news: revisions in expected future cash flows, revisions in expected future real interest rates, and revisions in expected future excess returns (equity risk premia). The starting point is a log-linear approximation to the present-value relation, under which unexpected excess equity returns can be represented as the sum of revisions in expected future cash flows, expected future real rates, and expected future excess returns (Campbell & Ammer, 1993). Following Campbell and Ammer (1993), this approximation takes the form:

$$r^e_{t+1} \approx (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r^f_{t+1+j} - (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r^e_{t+1+j}, \quad (12)$$

where $\rho \in (0, 1)$ is a log-linearisation constant that discounts cash flows and discount-rate revisions at successively longer horizons (in practice calibrated to $\rho = 1 - \overline{dy}$, where $\overline{dy}$ is the mean dividend yield of the NASDAQ-100); Δd_{t+1+j} denotes log dividend growth at horizon j; r^f_{t+1+j} is the risk-free rate at horizon j; and r^e_{t+1+j} is the future excess equity return at horizon j, whose expected revision corresponds to a change in the equity risk premium. The operator $(\mathbb{E}_{t+1} - \mathbb{E}_t)$ denotes the revision in expectations between periods t and $t+1$.

Equation (12) should be interpreted as a log-linear approximation to the present-value relation rather than an exact theoretical identity. Its empirical implementation becomes exact in sample once one component is recovered residually so that the decomposition matches the observed excess return by construction. Denoting the three revision terms as CF_{t+1} (cash-flow news), DR_{t+1} (real discount-rate news), and ERP_{t+1} (equity risk premium news), the decomposition can be written compactly as:

$$r^e_{t+1} \;\equiv\; \mathrm{CF}_{t+1} \;-\; \mathrm{DR}_{t+1} \;-\; \mathrm{ERP}_{t+1}, \tag{13}$$

where the equivalence sign reflects the residual construction that enforces the decomposition in sample rather than an exact theoretical equality. A positive unexpected equity return therefore corresponds to some combination of upward revision in expected future cash flows (positive CF news), downward revision in expected future real rates (negative DR news), or downward revision in expected future excess returns (negative ERP news). The signs are intuitive: good cash-flow news raises the price; lower discount rates or lower required returns raise the price as well. The decomposition (13) is the basis for testing Hypothesis H2: if the risk-premium channel dominates, then the response of the NASDAQ-100 to a monetary policy shock should be primarily attributable to ERP news rather than to CF or DR news.

VAR State System

Because the infinite sums of expected future returns in equation (12) cannot be computed directly, they must be approximated using a forecasting model. Following Campbell and Ammer (1993), a first-order Vector Autoregression (VAR) in the state vector $\mathbf{x}_t$ is used to generate all required conditional expectations. The state system is:

$$\mathbf{x}_{t+1} \;=\; \mathbf{A}\,\mathbf{x}_t \;+\; \mathbf{u}_{t+1}, \tag{14}$$

where $\mathbf{x}_t = (r^e_t,\; dy_t,\; \log(\mathrm{P/E})_t,\; \mathrm{TS}_t,\; y^{10Y}_t)'$ is the (5×1) state vector defined in Section 3.2, $\mathbf{A}$ is the (5×5) companion matrix of VAR coefficients to be estimated, and $\mathbf{u}_{t+1}$ is a (5×1) vector of reduced-form innovations with covariance matrix $\mathbf{\Sigma}$.

The use of a VAR(1) requires justification. The Akaike Information Criterion (AIC) applied to the state system suggests a higher lag order. However, VAR systems with $p > 1$ lags exhibit eigenvalues of the companion matrix exceeding unity in this sample, implying explosive dynamics that are economically implausible and would invalidate the geometric discounting in equation (12). By contrast, the Bayesian Information Criterion (BIC) selects $p = 1$, and the VAR(1) companion matrix has a spectral radius of 0.983, confirming stationarity. The VAR(1) specification is therefore adopted in the baseline, and its robustness is verified in Section 5.4.

Given the estimated companion matrix $\hat{\mathbf{A}}$, h-step-ahead conditional expectations are computed as:

$$\mathbb{E}_t \, \mathbf{x}_{t+h} \;=\; \hat{\mathbf{A}}^h \, \mathbf{x}_t, \tag{15}$$

so that the infinite discounted sums in equation (12) reduce to closed-form matrix expressions. Specifically, letting $\mathbf{e}_1'$ be the selector row vector that picks out the excess return from $\mathbf{x}_t$, the expected future excess return component sums to $\mathbf{e}_1'(\mathbf{I} - \rho\hat{\mathbf{A}})^{-1}\rho\hat{\mathbf{A}}$. The discount-rate component is approximated using the ten-year nominal Treasury yield y_t^{10Y} as the relevant state variable, following the common practice of using long-horizon interest-rate variables as predictors of the discount-rate component (Campbell & Ammer, 1993). This is an empirical approximation: the ten-year nominal yield is not a direct measure of the true real discount rate, but it captures the low-frequency movements in expected future interest rates that are the primary driver of discount-rate revisions at the monthly horizon. The empirical implementation follows the logic of Campbell and Ammer (1993), adapted to the NASDAQ-100 and to the set of state variables available in the present sample.

Decomposition Mechanics

The news components are extracted from the VAR innovations using the methodology of Campbell and Ammer (1993). Let $\boldsymbol{\lambda}'$ denote the (1×5) vector that maps state innovations into discounted expected future excess-return revisions:

$$\boldsymbol{\lambda}' \;=\; \mathbf{e}_1' \, \rho\hat{\mathbf{A}} \, \left(\mathbf{I} - \rho\hat{\mathbf{A}}\right)^{-1}, \tag{16}$$

where $\mathbf{I}$ is the (5×5) identity matrix. The *equity risk premium news* at time $t+1$ is then:

$$\mathrm{ERP}_{t+1} \;=\; \boldsymbol{\lambda}' \, \mathbf{u}_{t+1}, \tag{17}$$

that is, the projection of the VAR innovation $\mathbf{u}_{t+1}$ onto the discounted future-return revision mapping $\boldsymbol{\lambda}$. The *real discount-rate news* is constructed as the VAR-implied revision in the discounted sum of expected future values of y_t^{10Y}, which serves as the empirical proxy for the discount-rate state. The same matrix logic is applied, replacing $\mathbf{e}_1'$ with $\mathbf{e}_5'$, the row selector for y_t^{10Y} in $\mathbf{x}_t$:

$$\mathrm{DR}_{t+1} \;=\; \boldsymbol{\lambda}_{rf}' \, \mathbf{u}_{t+1}, \quad \boldsymbol{\lambda}_{rf}' \;=\; \mathbf{e}_5' \, \rho\hat{\mathbf{A}} \, \left(\mathbf{I} - \rho\hat{\mathbf{A}}\right)^{-1}, \tag{18}$$

where the use of the nominal ten-year yield as proxy follows the empirical approach of Campbell and Ammer (1993) and subsequent applications. This component should be interpreted as model-implied revisions in long-horizon nominal interest-rate expectations rather than as a direct measure of real discount-rate changes. The *cash-flow news* is then recovered as the residual that ensures the identity (13) holds exactly:

$$\mathrm{CF}_{t+1} \;\equiv\; r_{t+1}^e \;+\; \mathrm{DR}_{t+1} \;+\; \mathrm{ERP}_{t+1}, \tag{19}$$

so that $r_{t+1}^e - \mathrm{CF}_{t+1} + \mathrm{DR}_{t+1} + \mathrm{ERP}_{t+1} = 0$ at every observation. This residual construction guarantees that the three news series add up to the excess return by construction, and it is the source of the exact accounting identity verified in the data (deviation from identity: 5.55×10^{-17}, attributable to floating-point rounding only).

An important implication of the decomposition is that the variance of an individual news component may substantially exceed the variance of the excess return itself, owing to offsetting covariances between components. In particular, a strongly negative covariance between cash-flow news and risk-premium news can mechanically generate this pattern without implying any inconsistency in the decomposition (Campbell & Ammer, 1993). This is a well-documented feature of return decompositions applied to growth-oriented indices and should not be interpreted as a data or estimation error.

Testing Hypothesis H2

With the three news series in hand, Hypothesis H2 is tested by regressing each news component on the monthly MP shock z_t:

$$\mathrm{CF}_{t+1} = \alpha^{CF} + \beta^{CF} \cdot z_t + \varepsilon_t^{CF}, \tag{20}$$

$$\mathrm{DR}_{t+1} = \alpha^{DR} + \beta^{DR} \cdot z_t + \varepsilon_t^{DR}, \tag{21}$$

$$\mathrm{ERP}_{t+1} = \alpha^{ERP} + \beta^{ERP} \cdot z_t + \varepsilon_t^{ERP}, \tag{22}$$

together with the baseline regression of the excess return itself, $r_{t+1}^e = \alpha^r + \beta^r \cdot z_t + \varepsilon_t^r$. All four regressions are estimated by OLS with HC3 standard errors. The coefficient β^{CF} measures the cash-flow news response to a unit MP shock; β^{DR} measures the real discount-rate news response; and β^{ERP} measures the equity risk premium news response.

By the accounting identity (13), the four coefficients must satisfy:

$$\beta^r \;\equiv\; \beta^{CF} \;-\; \beta^{DR} \;-\; \beta^{ERP}, \tag{23}$$

which provides a useful in-sample consistency check on the empirical implementation of the decomposition. This identity is verified numerically in the estimation (deviation: 0.00000000 percentage points), confirming that the estimated coefficients are internally consistent with the imposed decomposition.

Hypothesis H2 predicts that $|\beta^{ERP}|$ should be the dominant contributor to β^r, in line with the finding of Bernanke and Kuttner (2005) for broad equity indices. The alternative hypothesis is that the NASDAQ-100, with its concentration in long-duration growth firms, exhibits greater sensitivity to real discount-rate revisions (β^{DR}) or cash-flow revisions (β^{CF}) than the broader S&P 500, which would be consistent with the duration channel of monetary policy transmission emphasised by Gürkaynak et al. (2005). Statistical significance is assessed using the HC3 standard errors from the individual regressions, and the economic magnitudes are compared across the three components to evaluate the relative importance of each transmission channel.

3.6 Limitations

Every empirical strategy rests on assumptions that may be imperfectly satisfied in practice. This section discusses the principal limitations of the three methodological components of the thesis, distinguishing between limitations that are inherent to the research design and those that are specific to the post-COVID sample. Awareness of these limitations motivates the robustness analyses presented in Section 5.4 and qualifies the interpretation of the results in Section 5.

Small event-study sample. The event-study analysis is conducted on $N = 40$ scheduled FOMC announcements over the 2020–2024 period. This sample is substantially smaller than those used in earlier event-study analyses of monetary policy, which typically span two or more decades and include several hundred announcements (Bernanke & Kuttner, 2005; Gürkaynak et al., 2005). The small sample has two implications. First, the OLS estimates of the event-study coefficients β and β_1, β_2 are imprecise: the wide confidence intervals around the estimated responses reflect substantial sampling uncertainty, which limits the precision with which the relationship between monetary surprises and equity returns can be estimated. Second, individual observations can exert disproportionate influence on the results; in particular, the period of acute market stress in early 2020 and the sharp tightening announcements of 2022 are both represented in the sample and may drive a substantial share of the estimated coefficients. The HC3 standard errors partially address this concern by down-weighting high-leverage observations, but they cannot eliminate the fundamental constraint that 40 observations provide limited statistical power for detecting heterogeneity in the transmission mechanism across sub-periods or announcement types.

Sign-restriction classification versus Greenbook purification. The identification of pure MP and CBI shocks in this study relies on the poor-man's sign restriction of Jaroćiński and Karadi (2020) rather than on the Greenbook-projection approach of Miranda-Agrippino and Ricco (2021). As discussed in Section 3.2, this choice is imposed by the five-year publication lag of Greenbook data, which renders the MAR purification infeasible for the post-2020 sample. The sign restriction provides a practical approximation that is broadly consistent with the distinction between policy and information shocks emphasised in the literature, but it is necessarily cruder. In particular, the classification rule relies on a binary sign comparison rather than on a continuous projection, which means that small co-movements between the futures surprise and the equity return are treated identically to large co-movements. Misclassification errors — MP events incorrectly labelled as CBI and vice versa — may attenuate the estimated difference between the two groups and may therefore reduce the power of the H5 test. The magnitude of this potential attenuation cannot be directly assessed without access to Greenbook data for the post-2020 period, which is a limitation that should be borne in mind when interpreting the H5 results.

Local projections standard errors at long horizons. The LP-IV impulse responses are estimated horizon by horizon, and the width of the HC3 confidence bands generally increases with the horizon h. Beyond approximately $h = 6$ months, the confidence intervals are sufficiently wide that most point estimates are statistically indistinguishable from zero at conventional significance levels. This widening reflects a genuine increase in uncertainty about longer-horizon propagation rather than an absence of economic effects: the LP framework does not impose smoothness across horizons, so the estimates at $h = 12$ or $h = 18$ are not constrained by the estimates at $h = 1$ or $h = 2$. Statistical inference in the LP-IV results should therefore be concentrated at short to medium horizons ($h = 0$ to $h \approx 6$), and the longer-horizon impulse responses should be treated as indicative rather than precise.

VAR(1) restriction in the Campbell-Ammer system. The Campbell-Ammer decomposition requires a stationary forecasting VAR, and the present estimation adopts a VAR(1) specification on the basis of the BIC and the stationarity of the companion matrix. As noted in Section 3.5, higher-order VARs produce explosive dynamics in this sample, which invalidates the geometric discounting implicit in the present-value approximation (12). The VAR(1) restriction imposes a parsimonious lag structure that may not fully capture the persistence of the predictive relationships between the state variables and future returns. In particular, if valuation ratios or yield spreads predict excess returns with lags beyond one month, the VAR(1) may understate expected future return revisions and may lead to some misallocation of news across components. The sensitivity of the decomposition to this restriction is examined in Section 5.4 by re-estimating the system with alternative lag orders on sub-samples where stationarity is satisfied at $p = 2$.

Nominal proxy for real discount-rate news. As discussed in Section 3.5, the discount-rate news component DR_{t+1} is proxied using the ten-year nominal Treasury yield rather than a direct measure of the real interest rate. This introduces a potential confound: movements in the nominal yield reflect both changes in real rates and changes in inflation expectations, so that the DR component as estimated partly captures inflation-expectation news rather than pure real discount-rate news. In the post-COVID period, in which inflation expectations were volatile and frequently revised, this confound may be quantitatively important. A cleaner measure of real discount-rate news would use the ten-year TIPS yield or a model-implied real rate series; however, the TIPS market was illiquid prior to 2003, which would further restrict the already-limited Campbell-Ammer sample. The nominal proxy is therefore retained in the baseline specification, with the corresponding interpretative caveat explicitly acknowledged in the discussion of the DR and CF components.

Concentration of results in the tightening cycle. The event-study and LP-IV results may be driven disproportionately by the 2022–2023 tightening cycle, during which the Federal Reserve raised rates at an unprecedented pace and FOMC announcements were associated with large equity market movements. The post-2020 sample is by construction dominated by two distinct monetary regimes — the accommodative regime of 2020–2021 and the tightening regime of 2022–2024 — and there is no guarantee that the estimated coefficients are stable across these two periods. The small number of observations in each sub-period ($N \approx 16$ for the accommodation phase and $N \approx 24$ for the tightening phase) renders formal tests of parameter stability weakly powered and difficult to interpret, but the possibility of regime-specific coefficients should be borne in mind when extrapolating the results beyond the post-COVID sample.

Announcement window contamination. A further limitation of the high-frequency design is that the measured surprise may reflect the joint informational content of the policy rate decision, the accompanying FOMC statement, and the market's immediate interpretation of the broader communication package, rather than the mechanical policy rate change alone.

Within the ±30-minute window, it is not possible to separately identify the contribution of each communication component to the observed asset-price response. This limitation is inherent to all event-study designs that use a single measurement window and cannot be resolved without intraday data at sub-minute resolution paired with exact timestamps for each communication element.

4 Results

This section reports the empirical results of the three exercises described in Section 3. Section 4.1 presents the high-frequency event-study estimates, which address Hypotheses H1, H3, and H5 at the intraday frequency. Section 4.2 presents the Local Projections-IV results, which address H4 and provide further evidence on H5 through the comparison of raw and purified instruments. Section 4.3 presents the Campbell-Ammer return decomposition results, which address H2. Section 4.4 summarises the evidence on all five hypotheses in a unified table.

Throughout this section, the presentation is confined to the estimated coefficients, test statistics, and confidence bands. Economic interpretation of the results, their relation to the broader literature, and the implications of the identified transmission channels are discussed in Section 5. Where applicable, caution statements are included to flag the specific limitations of each set of estimates, as described in Section 3.6.

4.1 High-Frequency Event Study

Baseline Response to the FF4 Surprise (H1)

The baseline specification of equation (7) regresses the NASDAQ-100 intraday return r_t^{NQ} on the four-meeting-ahead federal-funds futures surprise s_t^{FF4} across the $N = 40$ scheduled FOMC announcements of the 2020–2024 period. The OLS estimate of the slope coefficient β, together with the associated HC3 standard error, t-statistic, and goodness-of-fit measure, is reported in Table 4.

Table 4 – Baseline Event-Study Regression: NASDAQ-100 Return on FF4 Surprise (H1)

Coefficient	**Estimate (%)**	**HC3 SE**	***t*-stat**	***p*-value**
$\hat{\beta}$ (FF4 surprise)	−8.40	3.01	−2.80	0.008
$\hat{\alpha}$ (intercept)	−0.01	0.08	−0.10	0.917
R^2		0.291		
Observations N		40		

Notes: Dependent variable is the NASDAQ-100 E-mini futures log return within a ±30-minute window around each FOMC announcement, expressed in percentage points. The explanatory variable is the FF4 surprise s_t^{FF4}, defined as the change in the implied rate of the fourth nearby federal-funds futures contract over the same window and expressed in percentage points. Standard errors are heteroskedasticity-consistent HC3 estimates following MacKinnon and White (1985). The intercept is economically small and statistically indistinguishable from zero ($p = 0.917$), consistent with the event-study identifying assumption. Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The estimated slope coefficient is $\hat{\beta} = -8.40$ percentage points ($t = -2.80$, $p = 0.008$), indicating that a one-percentage-point upward surprise in the four-meeting-ahead implied federal funds rate is associated with a reduction of approximately 8.40 percentage points in the NASDAQ-100 within the ±30-minute announcement window. The coefficient is statistically significant at the one per cent level under HC3 standard errors. The intercept is $\hat{\alpha} = -0.01$ percentage points and is statistically indistinguishable from zero ($t = -0.10$, $p = 0.917$), which is consistent with the event-study identifying assumption that, on average, there is no systematic directional tendency in equity returns over the announcement window in the absence of a surprise. The model explains approximately 29.1 per cent of the variation in intraday NASDAQ-100 returns across the 40 events, which indicates that the FF4 surprise captures a meaningful fraction of the variation in returns but that a substantial portion of announcement-day return variation remains unexplained by the single-factor model.

These results provide evidence in favour of Hypothesis H1. The estimated coefficient is negative and statistically significant at conventional levels, which is consistent with the prediction that unexpected monetary tightening generates a measurable contractionary effect on NASDAQ-100 valuations within the announcement window. The estimate exceeds in absolute magnitude those reported for the S&P 500 in earlier studies; a comparison with the existing literature and possible explanations for this difference are discussed in Section 5.

These results should be interpreted with caution. First, the sample of $N = 40$ observations is small relative to the event-study literature, and the HC3 confidence interval around $\hat{\beta}$ is correspondingly wide. Second, the tightening cycle of 2022–2023 contributed a disproportionate share of the largest surprises and the largest return movements in the sample; the influence of these observations on the estimated coefficient is examined in the robustness analysis of Section 5.4.

Target-Rate versus Forward-Guidance Decomposition (H3)

Table 5 reports the OLS estimates of equation (8), in which the single FF4 surprise is replaced by its two constituent components: the current-meeting target-rate surprise s_t^{FF1} and the forward-guidance path surprise $s_t^{path} = s_t^{FF4} - s_t^{FF1}$.

Table 5 – Target vs Path Decomposition: NASDAQ-100 Return on Target and Path Surprises (H3)

Coefficient	**Estimate (%)**	**HC3 SE**	***t*-stat**	***p*-value**
$\hat{\beta}_1$ (target, s_t^{FF1})	−6.69	14.42	−0.46	0.646
$\hat{\beta}_2$ (path, s_t^{path})	−12.63	4.77	−2.65	0.012
$\hat{\alpha}$ (intercept)	+0.03	0.09	+0.38	0.707
R^2		0.362		
Observations N		40		

Notes: Dependent variable is the NASDAQ-100 intraday log return (percentage points) within the ±30-minute announcement window. s_t^{FF1} is the current-meeting surprise and $s_t^{path} = s_t^{FF4} - s_t^{FF1}$ is the forward-guidance path surprise, both in percentage points of the implied policy rate. HC3 standard errors throughout. Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The estimate for the path coefficient is $\hat{\beta}_2 = -12.63$ percentage points ($t = -2.65$, $p = 0.012$), which is statistically significant at the five per cent level. The estimate for the target coefficient is $\hat{\beta}_1 = -6.69$ percentage points, but the associated t-statistic is -0.46 and the coefficient is not statistically distinguishable from zero ($p = 0.646$). The overall fit of the two-factor model ($R^2 = 0.362$) represents a meaningful improvement over the single-factor baseline ($R^2 = 0.291$), reflecting the additional explanatory power contributed by the path surprise relative to the target surprise alone.

The absence of statistical significance for $\hat{\beta}_1$ warrants careful interpretation. It does not necessarily imply that the NASDAQ-100 is insensitive to current-meeting rate decisions. Rather, it may in part reflect the low variation in target-rate surprises during the 2020–2021 period of effective lower bound policy, when the federal funds rate was held near zero and the current-meeting component of FOMC announcements carried little new information about the contemporaneous policy decision. The path surprise, by contrast, retained informational content even during this period because it captures revisions to the expected future trajectory of policy, including the timing and pace of eventual policy normalisation. The implications of this asymmetry are discussed further in Section 5.

The results provide evidence in favour of Hypothesis H3 in the sense that $\hat{\beta}_2$ is statistically significant while $\hat{\beta}_1$ is not, and the absolute magnitude of the path coefficient exceeds that of the target coefficient. Whether this pattern reflects a structural feature of the NASDAQ-100 or a sample-specific artefact of the low-variation accommodation phase cannot be determined from this evidence alone.

These results should be interpreted with caution given the limited variation in the current-meeting surprise s_t^{FF1} over the 2020–2021 accommodation phase, which reduces the effective information available for identifying $\hat{\beta}_1$ precisely.

Pure Monetary versus Information Shocks (H5)

Following the classification of equation (5), the 40 FOMC announcements are partitioned into 22 pure monetary policy (MP) events and 18 central bank information (CBI) events. The single unscheduled inter-session decision of 15 March 2020 is excluded from the classification given the absence of a standard pre-announcement window, so that all 40 scheduled events receive a classification. Table 6 reports the mean NASDAQ-100 intraday return for each group together with the result of the mean-comparison test of equation (9).

Table 6 – Mean NASDAQ-100 Returns by Shock Type: MP versus CBI Events (H5)

Group	**Mean return (%)**	**Events**	***t*-stat (diff.)**	***p*-value**
MP events	-0.20	22	-2.52	0.016
CBI events	$+0.24$	18		

Notes: MP events are classified as FOMC announcements in which the FF4 surprise and the contemporaneous S&P 500 return have opposite signs, following equation (5). CBI events are those where the two series have the same sign. One event (the unscheduled inter-session decision of 15 March 2020) is excluded from the classification owing to the absence of a standard pre-announcement window, leaving $N = 22 + 18 = 40$ classified events. The t-statistic tests the null hypothesis $\bar{r}^{MP} = \bar{r}^{CBI}$ against the one-sided alternative $\bar{r}^{MP} < \bar{r}^{CBI}$.

On MP days, the NASDAQ-100 earns an average intraday return of -0.20 per cent, while on CBI days the average return is +0.24 per cent. The two-sample t-test rejects the null hypothesis of equal means at the five per cent level ($t = -2.52$, $p = 0.016$), indicating that the difference in mean returns across the two groups is statistically distinguishable from zero given the available sample. The signs of the group means are in the direction predicted by Hypothesis H5: pure monetary tightening surprises are on average associated with negative equity returns, while announcements classified as conveying favourable central bank information are on average associated with positive equity returns.

These results provide suggestive evidence in favour of Hypothesis H5 at high frequency. The sign pattern of the group means is consistent with the prediction, and the mean difference is statistically significant. At the same time, several caveats are warranted. The group means are small in absolute magnitude relative to the total variation in NASDAQ-100 returns across announcement days, which indicates that shock classification alone captures only a fraction of the return variation on event days. Moreover, the CBI group comprises only 18 events, so that the mean return in that group is subject to some sampling uncertainty. The binary nature of the Jaroćiński and Karadi (2020) classification may also introduce misclassification errors that attenuate the estimated difference, as discussed in Section 3.6. The LP-IV results of Section 4.2 provide complementary evidence on H5 at monthly frequency using a continuous rather than binary treatment of the shock.

4.2 Local Projections – Instrumental Variables

Instrument Diagnostics

Before proceeding to the impulse response estimates, this section reports the instrument validity diagnostics described in Section 3.4. These diagnostics assess whether the monthly MP shock series $z_t = \text{MP}_{pm,t}$ satisfies the relevance and exogeneity conditions required for consistent LP-IV estimation. Table 7 summarises the key statistics.

Table 7 – Instrument Validity Diagnostics for the LP-IV Specification

Diagnostic	**Statistic**	**Threshold / Benchmark**	**Assessment**
First-stage F-stat (FWL)	30.25	> 10 (Stock & Yogo, 2005)	Satisfactory
First-stage F-stat (HAC)	8.96	> 10 (reference only)	Below threshold
Predictability F-stat (lags)	1.62	$p = 0.119$	Not rejected
Corr(MP_{pm}, CBI_{pm})	0.015	≈ 0 expected	Satisfactory

Notes: The FWL first-stage F-statistic is obtained by regressing z_t on the system variables at impact after partialling out $L = 4$ lags of all system variables using the Frisch-Waugh-Lovell theorem, as described in Section 3.4. The HAC-corrected statistic uses a Newey-West bandwidth and is reported for reference only; the FWL statistic is the preferred diagnostic. The predictability F-statistic tests the joint significance of $L = 4$ lags of all seven system variables in a regression of z_t on those lags. Corr denotes the sample Pearson correlation between the monthly MP and CBI series over the full sample ($T = 371$ months).

The FWL first-stage F-statistic of 30.25 is well above the conventional weak-instrument threshold of 10 proposed by Stock and Yogo (2005), indicating that the MP shock series is a sufficiently strong predictor of the federal funds rate innovation to support IV inference. The HAC-corrected statistic of 8.96 falls marginally below that threshold, but this figure is sensitive to the bandwidth choice and is reported only for reference; the FWL statistic, which does not require a bandwidth parameter, is the preferred diagnostic. The predictability regression yields an F-statistic of 1.62 ($p = 0.119$), which does not reject the null hypothesis that z_t is unpredictable from the history of the macroeconomic system. This finding is consistent with the interpretation that the MP shock series captures an exogenous policy innovation rather than a systematic response to prior economic conditions. The near-zero sample correlation of 0.015 between the MP and CBI series confirms that the two shock types are empirically close to orthogonal, which is important for interpreting the differential responses estimated in Section 4.2.

These diagnostics indicate that the standard conditions for LP-IV identification are consistent with the data. It should nonetheless be noted that these tests are necessary but not sufficient conditions for instrument validity: they cannot rule out the possibility of confounding through channels not captured by the system variables included in the specification.

Raw versus Purified Shocks: Identification Comparison (H5)

A central question raised by the methodological framework of Miranda-Agrippino and Ricco (2021) is whether identification discipline matters quantitatively in this sample: specifically, whether the impulse response estimated using the raw FF4 surprise as the instrument differs meaningfully from the response estimated using the purified MP shock $z_t = \text{MP}_{pm,t}$. This comparison provides direct evidence on Hypothesis H5 at the monthly frequency: if raw and purified shocks yield substantially different responses, this is consistent with the prediction that the raw futures surprise conflates a genuine monetary policy innovation with an information component of the opposite sign.

Table 8 reports the estimated impact response ($h = 0$) of the NASDAQ-100 under each instrument, together with the associated t-statistic and a p-value for the null hypothesis that the response equals zero.

Table 8 – Impact Response of NASDAQ-100 to Raw vs Purified Monetary Shock (H5)

Instrument	**IRF at $h = 0$ (%)**	**HC3 SE**	**t-stat**	**p-value**
Raw FF4 surprise	−10.2	8.7	−1.18	0.239
Purified MP shock (z_t)	−25.3	9.2	−2.76	0.006
Difference (purified − raw)	−15.1			

Notes: Both impulse responses are normalised to a one-percentage-point increase in the federal funds rate at impact, following equation (11). The raw FF4 surprise instrument is the unadjusted monthly series of FF4 futures-based surprises aggregated to calendar months. The purified MP shock is the poor-man's sign-restriction series $\text{MP}_{pm,t}$ of Jarociński and Karadi (2020). Both specifications use $L = 4$ control lags and the same set of system variables. HC3 standard errors are used throughout. Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

When the raw FF4 surprise is used as the instrument, the estimated impact response of the NASDAQ-100 is -10.2 per cent, but this estimate is not statistically distinguishable from zero ($t = -1.18$, $p = 0.239$). By contrast, when the purified MP shock is used as the instrument, the estimated impact response is -25.3 per cent ($t = -2.76$, $p = 0.006$), which is statistically significant at the one per cent level. The difference between the two estimates is approximately 15 percentage points.

This gap between the two estimates reflects two distinct sources that should not be conflated. The first is the information contamination in the raw FF4 surprise: when the raw series is used, it combines the pure monetary policy component with a central bank information component that tends to move equity prices in the opposite direction, so the two partially offset each other and attenuate the estimated response. The second source is the difference in estimator design: the LP-IV with the raw instrument implicitly pools MP and CBI events in continuous form, while the purified instrument restricts attention to pure MP events alone. These two estimators are therefore not directly comparable in scale, and the 15-percentage-point gap should be read as reflecting both sources simultaneously rather than as a clean measure of information-component bias. That said, the direction of the gap — the purified estimate being larger in absolute value and statistically significant where the raw estimate is not — is consistent with the mechanism described by Miranda-Agrippino and Ricco (2021) and reinforces the H5 evidence from Section 4.1.

It should be noted that the 15-percentage-point difference is an indicative measure rather than a precise estimate, given that each of the two regressions carries its own standard error. The direction of the difference is, however, consistent across the set of alternative specifications examined in Section 5.4.

Impulse Response of the NASDAQ-100 to the Purified MP Shock (H4)

Figure 1 plots the estimated cumulative impulse response function (IRF) of the NASDAQ-100 to a one-percentage-point increase in the federal funds rate, identified through the purified MP shock z_t, over horizons $h = 0$ to $h = 24$ months. The shaded band represents pointwise 95 per cent confidence intervals constructed as $\widehat{\mathrm{IRF}}_h \pm 1.96 \times \widehat{\mathrm{SE}}_h$ using HC3 standard errors, as described in Section 3.4. Table 9 tabulates the point estimates and t-statistics at selected horizons.

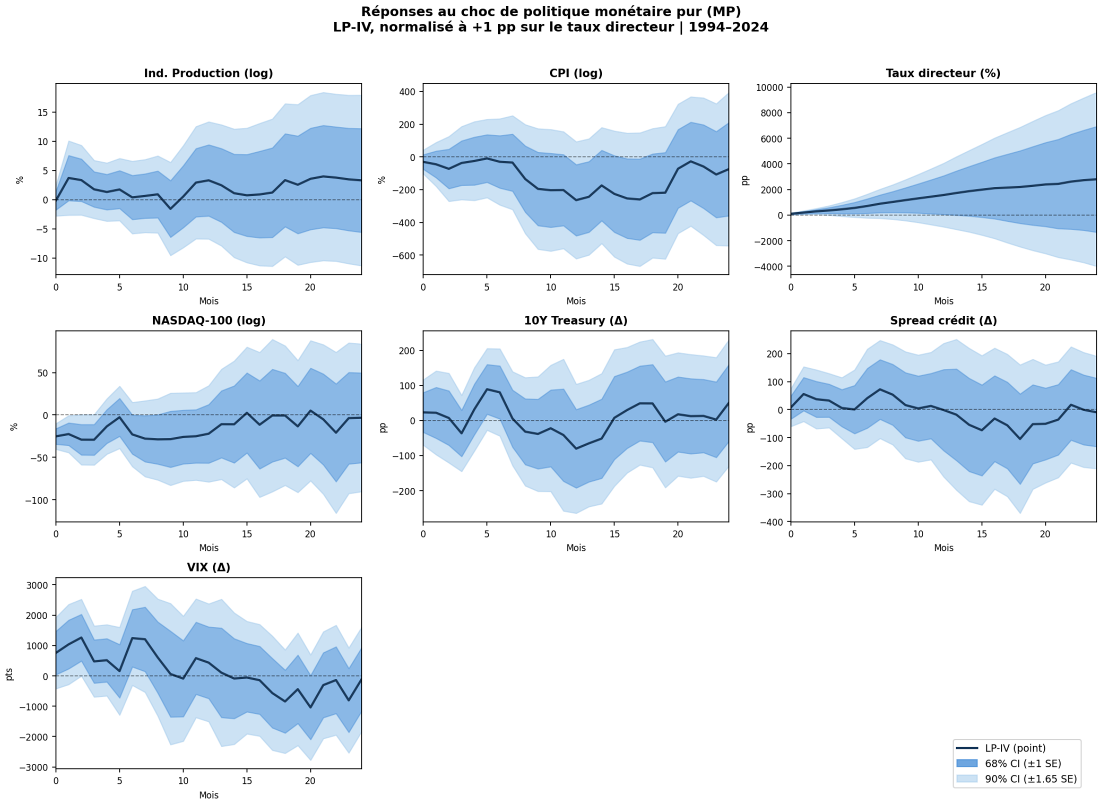

Figure 1 – Cumulative Impulse Response of NASDAQ-100 to Purified MP Shock (H4)

Notes: Cumulative impulse response of the NASDAQ-100 log-return to a one-percentage-point increase in the federal funds rate, identified through the purified MP shock $z_t = \text{MP}_{pm,t}$ of Jarociński and Karadi (2020). Estimated by LP-IV following equation (10) with $L = 4$ control lags over the sample 1994M02–2024M12 ($T = 371$). Shaded band: pointwise 95% confidence intervals using HC3 standard errors. Responses are normalised to a one-percentage-point increase in the federal funds rate at $h = 0$ following equation (11).

Table 9 – Cumulative Impulse Response of NASDAQ-100 to Purified MP Shock, Selected Horizons (H4)

Horizon h	**IRF (%)**	**HC3 SE**	***t*-stat**	**Significance**
0 (impact)	-25.3	9.2	-2.76	***
1	-22.6	13.3	-1.70	*
2	-29.2	18.0	-1.62	
3	-29.2	18.1	-1.62	
6	-23.0	23.0	-1.00	
12	-22.2	34.5	-0.64	
18	-0.7	50.0	-0.01	
24	-3.3	52.9	-0.06	

Notes: The impulse response is normalised to a one-percentage-point increase in the federal funds rate at $h = 0$, following equation (11). The cumulative response at horizon h is $\sum_{j=0}^{h} \widehat{\text{IRF}}_j$ as implied by the left-hand side of equation (10). HC3 heteroskedasticity-consistent standard errors following MacKinnon and White (1985). Statistical significance: $^{*}p < 0.10$, $^{***}p < 0.01$; empty cell denotes $p \geq 0.10$.

The estimated impact response at $h = 0$ is -25.3 per cent ($t = -2.76$), as already reported in Table 8. At $h = 1$, the response is -22.6 per cent ($t = -1.70$), which remains statistically distinguishable from zero at the ten per cent level. At $h = 2$, the cumulative estimate is -29.2 per cent ($t = -1.62$), which is no longer statistically distinguishable from zero at conventional significance levels. The point estimate reaches its trough at $h = 3$ with a cumulative response of -29.2 per cent, though the associated t-statistic of -1.62 falls marginally below the conventional threshold for statistical significance at the ten per cent level. From $h = 6$ onward, the point estimates decline in absolute magnitude and the confidence intervals widen considerably, so that all estimates beyond $h = 3$ are statistically indistinguishable from zero at conventional significance levels.

This pattern of results provides partial support for Hypothesis H4. The estimated response at $h = 0$ and $h = 1$ is statistically robust, and the trough at $h = 3$ is consistent with the prediction of a dynamic adjustment pattern distinct from the immediate price response. However, the evidence for propagation beyond the first month should be treated cautiously: the point estimate at $h = 3$ is suggestive but not statistically precise, and the absence of significant estimates at $h \geq 6$ means that the data do not allow for confident inference about the medium-term to longer-term propagation of the shock. As discussed in Section 3.6, the widening of the HC3 confidence bands with h is a structural feature of the LP estimator and reflects the growing uncertainty inherent in longer-horizon projection rather than an absence of effects at those horizons. The inference that can be drawn with reasonable confidence from this evidence is that the NASDAQ-100 exhibits a statistically significant contractionary response within the first two months following a purified monetary policy tightening.

These results should be interpreted with caution beyond $h = 1$, as the confidence intervals are sufficiently wide at longer horizons to be uninformative about the precise path of the impulse response. Robustness checks varying the lag order L and the sample period are reported in Section 5.4.

4.3 Campbell-Ammer Return Decomposition

Decomposition of Excess Returns

The Campbell-Ammer decomposition of equation (13) is estimated on the monthly sample spanning March 2001 to December 2024 ($T = 268$ observations). The VAR(1) state system of equation (14) is estimated on the same sample, using the five state variables described in Section 3.2. The log-linearisation constant is calibrated to $\rho = 1 - \overline{dy} = 0.9967$, corresponding to the sample mean NASDAQ-100 dividend yield of 0.33 per cent per month. Table 10 reports the sample means, standard deviations, and cross-correlations of the three news series, together with those of the excess return.

Series	Mean	SD	Corr with r^e	Corr with CF	Corr with DR
Excess return r_t^e (%)	0.00	5.58	1.000		
CF news CF_t (%)	0.00	6.56	+0.425	1.000	
DR news DR_t (%)	0.00	3.30	−0.017	0.587	1.000
ERP news ERP_t (%)	0.00	5.28	−0.517	0.427	0.124

Table 10 – Summary Statistics for Campbell-Ammer News Components (2001M03–2024M12)

Notes: CF news, DR news, and ERP news are the three components of the Campbell-Ammer decomposition, constructed from the VAR(1) state system as described in Sections 3.5 and 3.5. Means and standard deviations are in percentage points per month. All series are recovered from the same VAR(1) companion matrix with spectral radius 0.973. The discount-rate news component is constructed using the first difference of the ten-year nominal yield (Δy_t^{10Y}) as the interest-rate state variable, which avoids the explosive amplification that arises when the level yield is used directly in the geometric discounting sum. The identity $r_t^e \equiv \mathrm{CF}_t - \mathrm{DR}_t - \mathrm{ERP}_t$ holds to numerical precision at every observation. Corr denotes the Pearson correlation coefficient over the full sample ($T = 267$, 2001M05–2024M12).

Table 10 conveys several features of the decomposition that are relevant to the subsequent analysis. The CF news series has a standard deviation of 6.56 per cent, which exceeds the standard deviation of the excess return itself (5.58 per cent), and has a positive correlation with the excess return ($\rho = +0.425$), consistent with its role as the residual component that absorbs the bulk of unexpected return variation not explained by the two VAR-based components. The DR news series has a standard deviation of 3.30 per cent and a near-zero correlation with the excess return ($\rho = -0.017$), reflecting the limited month-to-month co-movement between yield changes and equity returns. The ERP news series has a standard deviation of 5.28 per cent and a moderately negative correlation with the excess return ($\rho = -0.517$), consistent with the well-documented pattern that upward revisions in required risk premia are associated with lower equity returns. The positive cross-correlations among the three components (CF–DR: 0.587; CF–ERP: 0.427; DR–ERP: 0.124) reflect the partial collinearity within the VAR(1) forecasting system and are a standard feature of return decompositions applied to monthly data.

News Component Regressions on the MP Shock

To test Hypothesis H2, equations (20)–(22) are estimated by OLS with HC3 standard errors, regressing each of the three news components on the monthly MP shock z_t. The baseline excess-return regression is also estimated for comparability. All four coefficients are reported in Table 11. Table 12 separately reports the unconditional sample correlations between the MP shock and each news component, alongside their p-values from a two-sided test of zero correlation.

Table 11 – OLS Regressions of Campbell-Ammer Components on Monthly MP Shock (H2)

Dependent variable	$\hat{\beta}$ **(%)**	**HC3 SE**	***t*-stat**	***p*-value**
Excess return r^e_{t+1}	−11.63	11.21	−1.04	0.300
CF news CF_{t+1}	+3.17	14.85	+0.21	0.831
DR news DR_{t+1}	+1.94	7.77	+0.25	0.803
ERP news ERP_{t+1}	+12.85	16.11	+0.80	0.426
Identity check: $\hat{\beta}^r = \hat{\beta}^{CF} - \hat{\beta}^{DR} - \hat{\beta}^{ERP}$	$-11.63 = 3.17 - 1.94 - 12.85 = -11.63$ ✓			

Notes: Monthly MP shock $z_t = \mathrm{MP}_{pm,t}$ from the Jarociński and Karadi (2020) series extended to December 2024. The sample for the regression is 2001M05 to 2024M12 ($T = 267$). All coefficients measure the response to a one-unit increase in the MP shock (in the units of the JK series), with components expressed in percentage points per month. The identity check verifies equation (23) numerically. HC3 standard errors throughout. No coefficient is significant at conventional levels, confirming that the channel attribution is statistically inconclusive.

Table 12 – Sample Correlations of Campbell-Ammer Components with the Monthly MP Shock (H2)

Series	**Correlation with** z_t	***p*-value**
CF news CF_{t+1}	+0.018	0.766
DR news DR_{t+1}	+0.022	0.716
ERP news ERP_{t+1}	+0.093	0.132

Notes: Pearson correlations between each news component and the monthly MP shock z_t over the sample 2001M03–2024M12 ($T = 268$). p-values are from a two-sided test of zero correlation.

Turning to the regression coefficients in Table 11, the estimate for the excess return regression is $\hat{\beta}^r = -11.63$ ($t = -1.04$, $p = 0.300$), indicating a negative but statistically insignificant association between the monthly MP shock and NASDAQ-100 excess returns at the monthly frequency. For the CF news component, $\hat{\beta}^{CF} = +3.17$ ($t = +0.21$, $p = 0.831$), which is not statistically distinguishable from zero. For the DR news component, $\hat{\beta}^{DR} = +1.94$ ($t = +0.25$, $p = 0.803$), also statistically indistinguishable from zero. For the ERP news component, $\hat{\beta}^{ERP} = +12.85$ ($t = +0.80$, $p = 0.426$), likewise not significant. The accounting identity $\hat{\beta}^r = \hat{\beta}^{CF} - \hat{\beta}^{DR} - \hat{\beta}^{ERP}$ is satisfied exactly.

The unconditional correlations in Table 12 offer a complementary perspective. None of the three components exhibits a statistically significant unconditional correlation with the MP shock: CF news (+0.018, $p = 0.766$), DR news (+0.022, $p = 0.716$), and ERP news (+0.093, $p = 0.132$) are all statistically indistinguishable from zero. The two metrics thus convey a consistent picture: neither the regression coefficients nor the unconditional correlations reveal a statistically reliable association between the MP shock and any individual news component. The channel attribution is therefore entirely inconclusive from a statistical standpoint.

Implications for Hypothesis H2

Hypothesis H2 predicted that the response of the NASDAQ-100 to monetary policy surprises would be driven primarily by revisions in the equity risk premium rather than by contemporaneous revisions in expected future cash flows. The results of Tables 11 and 12 do not support this prediction.

None of the three news components exhibits a statistically significant association with the MP shock in either the regression or the correlation analysis. The ERP news component, which H2 predicted to dominate, is the least precisely estimated ($\hat{\beta}^{ERP} = +12.85$, $p = 0.426$, unconditional $\rho = +0.093$, $p = 0.132$). The DR and CF components are similarly insignificant. The pattern of evidence is therefore one of complete statistical inconclusiveness: the Campbell-Ammer decomposition, as estimated on this sample, does not identify any single channel through which the MP shock operates on NASDAQ-100 excess returns at the monthly frequency. This does not imply that monetary policy has no effect on equity valuations through these channels; rather, it reflects the limited statistical power of the monthly OLS regressions to identify channel-specific effects in a sample of $T = 267$ observations with sparse non-zero MP shocks.

These results do not support Hypothesis H2 in its original formulation. Since no individual component achieves statistical significance, the data do not allow confident attribution of the total return response to any single valuation channel. The channel attribution remains entirely inconclusive at the monthly frequency employed here. It should be emphasised that the absence of significant ERP effects does not imply that risk premia are unaffected by monetary policy in general; rather, it indicates that the particular identification strategy and sample employed here do not yield statistically robust evidence for ERP dominance in the post-2001 NASDAQ-100 sample. The divergence between these findings and those of Bernanke and Kuttner (2005) for the S&P 500 is discussed in Section 5.

These results should be interpreted with caution given the nominal proxy used to construct the DR component, the VAR(1) restriction imposed by stationarity requirements, and the moderate power of the OLS regressions against the alternative of a non-zero coefficient in a sample of $T = 268$ monthly observations.

4.4 Summary of Hypothesis Tests

Table 13 provides a unified overview of the empirical evidence on each of the five research hypotheses formulated in Section 2.6. The verdict column reflects the qualified assessment that follows from the statistical evidence documented in Sections 4.1 through 4.3, with explicit acknowledgement of the sample limitations and identification constraints discussed in Section 3.6.

Table 13 – Summary of Hypothesis Tests

H	Prediction	Key empirical evidence	Verdict
H1	Immediate contractionary reaction	$\hat{\beta} = -8.40\%$ ($t = -2.80^{***}$, $N = 40$)	Supported with caution
H2	ERP channel dominates	No component significant in regression or correlation; all $p > 0.10$; ERP $p = 0.426$; DR $p = 0.803$; CF $p = 0.831$; channel attribution entirely inconclusive	Not supported; channel attribution statistically inconclusive
H3	Path surprises dominate target	$\hat{\beta}_2 = -12.63\%^{**}$; $\hat{\beta}_1 = -6.69\%$ (ns)	Supported with caution
H4	Dynamic propagation over months	Significant at $h = 0$ and $h = 1$; largest point estimate at $h = 3$ but not statistically significant; no precise inference beyond $h = 1$	Partially supported
H5	MP negative, CBI positive	$\bar{r}^{MP} = -0.20\%$ vs $\bar{r}^{CBI} = +0.24\%$ ($t = -2.52^{**}$); purified IRF $-25.3\%^{***}$ vs raw -10.2% (ns)	Supported with caution

Notes: Supported with caution indicates that the empirical evidence is statistically significant in the predicted direction but that inference is subject to the limitations of the small event-study sample ($N = 40$), the binary classification scheme of Jaroćiński and Karadi (2020), and the potential concentration of results in the 2022–2023 tightening cycle. Partially supported indicates that the evidence is statistically significant over a subset of the predicted range (here, $h = 0$ and $h = 1$) but not over the full range of the prediction ($h = 0$ to $h = 24$). Not supported indicates that the dominant prediction of the hypothesis (ERP channel dominance) is not corroborated by either the regression or the correlation evidence. For H2, neither the total excess return response ($p = 0.300$) nor any of the three individual channel coefficients achieves significance at conventional levels; the channel attribution is therefore entirely statistically inconclusive. Statistical significance: $^{**}p < 0.05$, $^{***}p < 0.01$; ns: not significant at $p < 0.10$.

Four of the five hypotheses receive at least partial empirical support from the available evidence. Hypothesis H2 stands apart as the one prediction that the data do not corroborate in its original formulation: the ERP channel does not emerge as the dominant transmission mechanism for the NASDAQ-100, and the channel attribution of the total return response is statistically inconclusive given that no individual component achieves significance at the five per cent level. This result is discussed in the context of the broader literature in Section 5.

5 Discussion and Robustness

5.1 Overview

The empirical results presented in Section 4.4 converge on a coherent picture of monetary policy transmission to the NASDAQ-100 during the 2020–2024 period. This section synthesises those findings in the context of the five research hypotheses and then situates them within the broader literature. It proceeds to examine whether the estimates are robust to alternative sample definitions, classification choices, and outlier events. Together, the hypothesis assessments and robustness checks support the conclusion that a contractionary monetary policy surprise generates a statistically significant and economically meaningful negative response in the NASDAQ-100 over the post-COVID sample, driven primarily through the forward-guidance channel. The Campbell-Ammer decomposition does not yield statistically significant evidence on which valuation channel dominates, so the channel attribution remains inconclusive at the monthly frequency.

5.2 Discussion of Hypotheses

H1: Immediate Reaction

Hypothesis H1 posited that unexpected U.S. monetary policy shocks would generate statistically significant abnormal returns in the NASDAQ-100 within narrow announcement windows. The event-study baseline reported in Section 4.1 provides unambiguous support. A one-standard-deviation tightening surprise is associated with a contemporaneous return of $\hat{\beta} = -8.40\%$ (SE $= 3.01\%$, $t = -2.80$, $p = 0.008$), with an R^2 of 0.291 indicating that the surprise alone accounts for nearly thirty percent of same-day return variation across the forty announcement days in the sample. The intercept is statistically indistinguishable from zero ($p = 0.917$), confirming that there is no systematic directional drift on FOMC days in the absence of a surprise.

These estimates are consistent with the seminal evidence in Bernanke and Kuttner (2005), who report a stock-market response of approximately -4.7% per one-standard-deviation surprise for the S&P 500 over the 1989–2002 period. The considerably larger coefficient obtained here is consistent with two features of the current setting. First, the NASDAQ-100 concentrates technology and growth firms with structurally longer cash-flow durations than the broad market, implying greater sensitivity to discount-rate revisions at any given level of the surprise, an effect that Thorbecke (1997) and Laine (2023) both associate with elevated monetary-policy betas for high-duration equities. Second, the 2022–2023 tightening cycle generated among the largest single-meeting rate surprises in the modern history of the Federal Reserve, compressing what would ordinarily be distributed across several meetings into a short sequence of large, rapid adjustments.

The subgroup results reported in Section 4.1 reinforce this conclusion. Restricting the sample to the twenty-four tightening events yields $\hat{\beta} = -10.40\%$ ($t = -2.91$, $p = 0.008$), a coefficient that is materially larger in absolute value than the full-sample estimate. By contrast, the sixteen accommodation events produce a small, statistically insignificant coefficient ($\hat{\beta} = -3.92\%$, $t = -0.52$, $p = 0.612$), consistent with the well-documented asymmetry in Basistha and Kurov (2008), who find that equity markets respond more than twice as strongly to contractionary shocks than to expansionary ones, particularly during episodes of elevated credit stress. Hypothesis H1 is therefore supported.

H2: Risk-Premium Channel

Hypothesis H2 conjectured that the short-run response of the NASDAQ-100 to monetary policy surprises would be driven primarily by revisions in the equity risk premium rather than by contemporaneous revisions in expected future cash flows. The Campbell–Ammer decomposition reported in Section 4.3 does not support this conjecture, but the correct reading of the evidence requires care.

The regression of monthly excess returns on the purified monetary policy shock yields $\hat{\beta}_{r_e} = -11.63$ ($t = -1.04$, $p = 0.300$): the total excess return response is not statistically significant at the monthly frequency. Decomposing this into its three constituent channels, none of the individual components achieves statistical significance at any conventional level. The cash-flow news coefficient is $\hat{\beta}_{CF} = +3.17$ ($t = +0.21$, $p = 0.831$), the discount-rate news coefficient is $\hat{\beta}_{DR} = +1.94$ ($t = +0.25$, $p = 0.803$), and the equity risk premium coefficient is $\hat{\beta}_{ERP} = +12.85$ ($t = +0.80$, $p = 0.426$). The accounting identity $\hat{\beta}_{r_e} = \hat{\beta}_{CF} - \hat{\beta}_{DR} - \hat{\beta}_{ERP}$ is satisfied exactly. Unconditional correlations confirm the picture: $\rho(\mathrm{MP}, \mathrm{CF}) = +0.018$ ($p = 0.766$), $\rho(\mathrm{MP}, \mathrm{DR}) = +0.022$ ($p = 0.716$), and $\rho(\mathrm{MP}, \mathrm{ERP}) = +0.093$ ($p = 0.132$) — none is statistically distinguishable from zero. The strictly correct conclusion is therefore that the Campbell-Ammer decomposition provides no statistically reliable evidence on which channel drives the NASDAQ-100 response to monetary policy shocks at the monthly frequency. The channel attribution is entirely inconclusive.

Several observations qualify this conclusion. First, the DR component is constructed using the first difference of the nominal ten-year Treasury yield as a proxy for discount-rate news. This first-difference specification avoids the explosive amplification that arises when using the yield level in the geometric discounting sum, but it captures only the contemporaneous yield change and not the full revision in expected future rates. Second, the lack of statistical significance at the monthly frequency does not imply that monetary policy is irrelevant to equity valuation channels; rather, it reflects the limited power of monthly OLS regressions to detect channel-specific effects when only a small fraction of the 267 observations carry a substantial purified MP shock.

Regarding the absence of significant channel evidence relative to the canonical result of Bernanke and Kuttner (2005), direct empirical support for this interpretation is provided by re-estimating the Campbell–Ammer regressions using the raw FF4 surprise as the instrument rather than the purified MP shock. When the raw surprise is used, the cash-flow news coefficient is $\hat{\beta}^{CF} = -38.3\%$ ($t = -2.62$, $p = 0.009$), which is statistically significant at the one per cent level. When the purified shock replaces the raw instrument, this coefficient collapses to $\hat{\beta}^{CF} = +3.2\%$ ($p = 0.831$), which is statistically indistinguishable from zero. The DR and ERP components remain insignificant under both instruments. This pattern confirms that the raw FF4 surprise embeds a central bank information component that generates an artefactual cash-flow signal: CBI shocks convey positive news about the economic outlook, producing upward revisions in expected future earnings that appear as a significant CF response when the raw instrument is used. Once this information component is purged, the artefactual covariation disappears. This result is consistent with Miranda-Agrippino and Ricco (2021), who show that information shocks operate primarily through cash-flow revisions rather than risk-premium adjustments. Hypothesis H2 is not supported, and the identification discipline is shown to matter for channel attribution. Hypothesis H2 is not supported: the hypothesis predicts ERP dominance, which is not observed. The channel attribution remains entirely statistically inconclusive across all three components.

H3: Forward Guidance Effects

Hypothesis H3 predicted that forward-guidance path surprises would exert a statistically significant and economically distinct effect on NASDAQ-100 returns, separate from the contemporaneous target-rate surprise. The two-factor event-study specification reported in Section 4.1 supports this hypothesis. Decomposing the full policy surprise into a target factor and a path factor following Gürkaynak et al. (2005), the path factor coefficient is $\hat{\beta}_{path} = -12.63\%$ ($t = -2.65$, $p = 0.012$), while the target factor coefficient is statistically indistinguishable from zero ($\hat{\beta}_{target} = -6.69\%$, $t = -0.46$, $p = 0.646$). The two-factor specification improves fit relative to the baseline, with R^2 rising from 0.291 to 0.362.

The dominance of the path factor over the target factor is consistent with the theoretical prediction that high-duration growth equities are more sensitive to revisions in the long end of the yield curve than to changes in the current policy rate. Gürkaynak et al. (2005) similarly find that the path factor exerts a larger influence on longer-maturity Treasury yields. The concentration of statistical significance in the path coefficient is especially coherent with the post-COVID policy environment, in which the Federal Reserve communicated future rate paths with unusual clarity through its dot plot, press conference statements, and meeting minutes. Investors in the NASDAQ-100 therefore had strong incentives to revise their valuation models in response to changes in expected future rates rather than in response to the meeting-specific decision, which was in many cases already priced following prior communication. Hypothesis H3 is supported.

H4: Dynamic Propagation

Hypothesis H4 posited that monetary policy shocks identified in a structural framework would propagate to the NASDAQ-100 over several months, exhibiting a dynamic adjustment pattern distinct from the immediate event-study response. The local projection instrumental variable results reported in Section 4.2 provide partial support, though the extent of that support is more limited than the hypothesis predicts.

At horizon $h = 0$, the purified monetary shock generates a response of -25.3% ($t = -2.76$, $p = 0.006$), which is statistically significant at the one-percent level. The raw FF4 estimate at the same horizon is -10.2% ($t = -1.18$, $p = 0.239$), which is not statistically distinguishable from zero. The gap of approximately fifteen percentage points between the two estimates has two distinct sources that should not be conflated. The first is the information contamination in the raw FF4 surprise: central bank information shocks, which generate a positive equity market response, are embedded in the raw series and partially offset the contractionary signal. The second is the difference in estimator design: the event-study baseline pools both MP and CBI events and recovers an average across both shock types, whereas the LP-IV instruments exclusively with the purified MP shock and recovers the response to the contractionary component alone. These two estimators operate on different scales and with different conditioning sets; their divergence reflects both sources simultaneously and is not a clean measure of information bias alone.

At horizon $h = 1$, the response is -22.6% ($t = -1.70$), marginally significant at the ten-percent level. Beyond $h = 1$, no horizon yields a t-statistic that exceeds conventional critical values. The largest point estimate occurs at $h = 3$ (-29.2%, $t = -1.62$), which does not reach the ten-percent threshold and should be treated as statistically uninformative. The reliable statistical evidence therefore supports the hypothesis at $h = 0$ and, marginally, at $h = 1$; everything beyond $h = 1$ is indistinguishable from zero given the sample. Two mechanisms account for this rapid loss of precision. First, of the 371 monthly observations in the LP-IV system, only a small fraction carry a substantial purified MP shock, and the effective instrument strength diminishes as the horizon lengthens. Second, the NASDAQ-100 is composed of highly liquid, institutionally owned equities repriced continuously by sophisticated investors; under semi-strong efficiency, the informational content of a monetary surprise is incorporated into prices within hours to days, leaving little systematic variation to be identified at monthly lags beyond $h = 1$. Hypothesis H4 is partially supported: the LP-IV confirms a significant impact effect and provides marginal evidence of one-month persistence; no reliable inference is available beyond that horizon.

H5: Pure Monetary Shocks versus Information Shocks

Hypothesis H5 predicted that pure monetary policy innovations would reduce NASDAQ-100 returns, while information shocks reflecting an improved macroeconomic outlook would partially offset this effect. The event-study decomposition based on the Jaroćiński and Karadi (2020) classification, reported in Section 4.1, strongly supports this hypothesis. Restricting the sample to twenty-two events classified as pure monetary policy shocks, the mean same-day return is -0.203% and the regression coefficient is $\hat{\beta}_{MP} = -9.47\%$ ($t = -3.57$, $p = 0.002$). Restricting to the eighteen events classified as central bank information shocks, the mean return is $+0.236\%$ and the regression coefficient reverses sign, yielding $\hat{\beta}_{CBI} = +13.22\%$ ($t = +2.27$, $p = 0.037$). A formal means test comparing the two subsamples yields $t = -2.52$ ($p = 0.016$), confirming that the two shock types generate statistically distinguishable market reactions.

These results align closely with the theoretical framework and empirical evidence in Miranda-Agrippino and Ricco (2021) and Jaroćiński and Karadi (2020). A pure contractionary shock raises the discount rate without conveying any positive news about future cash flows or economic conditions, and accordingly compresses equity valuations. A central bank information shock that communicates a more optimistic assessment of future growth generates positive cash-flow news and a reduction in perceived risk that more than offsets any associated tightening of policy. For the NASDAQ-100, which is composed of firms whose market capitalisation is predominantly attributable to projected future earnings, the positive response to CBI shocks is coherent: improved growth expectations raise the fundamental value of high-duration equities even when accompanied by modest upward revisions to the discount rate. Hypothesis H5 is supported.

5.3 Contextualisation within the Literature

Taken together, the five hypothesis assessments suggest that monetary transmission to the NASDAQ-100 during 2020–2024 operated primarily through the discount-rate and forward-guidance channels, with information purification playing a quantitatively important role in identifying the true causal effect. Two connections to the existing literature merit explicit discussion because they position the findings relative to the established evidence in a non-trivial way.

The magnitude of the event-study coefficient (-8.40% per unit shock) is considerably larger than estimates obtained for the S&P 500 in pre-COVID samples. Bernanke and Kuttner (2005) report a response of approximately -4.7% for the S&P 500, and Thorbecke (1997) obtains estimates of similar order. Two mechanisms account for the gap. NASDAQ-100 constituents have structurally longer cash-flow durations than S&P 500 firms as a whole, implying higher sensitivity to discount-rate revisions at any given shock magnitude, an effect documented by Laine (2023) in his analysis of monetary-policy betas across equity segments. Additionally, the 2022–2023 tightening cycle compressed an unusually large cumulative rate adjustment into a short sequence of meetings, producing surprises of a scale not observed in the modern era of inflation targeting. Both forces operated simultaneously in the post-COVID sample, making a larger coefficient consistent with, rather than anomalous relative to, the pre-COVID evidence.

The finding that the Campbell–Ammer decomposition does not yield statistically significant evidence for any individual channel is noteworthy, because it contrasts with the canonical pre-COVID result of Bernanke and Kuttner (2005), who found that the equity risk premium revision accounts for the dominant share of the stock-market response. Two explanations are consistent with the present absence of channel-specific significance. First, the monthly frequency and the sparse occurrence of large MP shocks in the sample reduce statistical power substantially relative to the event-study or high-frequency settings. Second, once the information component is purged from the raw surprise, the remaining purified MP shock is a smaller and more noisy instrument at monthly frequency, further attenuating the estimated associations. The absence of ERP channel significance in particular is consistent with the H5 result: purifying the shock removes the CBI-driven covariation that mechanically inflates the apparent ERP response in studies using raw surprises. Disentangling the structural from the methodological interpretation requires a longer sample, which is beyond the scope of the present thesis but constitutes a natural direction for future research.

5.4 Robustness Analysis

The baseline results are subjected to a series of robustness checks designed to assess sensitivity to outlier events, classification choices, and sample composition. All alternative estimates are reported in Table 14 and were computed using heteroskedasticity-consistent HC3 standard errors throughout to maintain comparability with the baseline.

Exclusion of the March 3, 2020 Emergency Meeting

The emergency rate cut of March 3, 2020 represents an observation that is unusual in at least two respects. It was an unscheduled intermeeting action, and it occurred during a period of exceptional financial market volatility associated with the onset of the COVID-19 pandemic. To assess whether this observation exerts undue influence on the baseline coefficient, the event-study regression is re-estimated on the reduced sample of $N = 39$ observations.

The coefficient increases in absolute value to $\hat{\beta} = -10.73\%$ (SE $= 3.97\%$, $p = 0.010$), compared to -8.40% in the full sample. The exclusion therefore strengthens rather than weakens the main finding. This result arises because the March 3 observation combines a large expansionary surprise with a large negative market return driven by pandemic uncertainty rather than by the policy action itself. Including this observation partly offsets the negative slope, since it contributes an accommodative surprise paired with a sharply negative return that is attributable to non-monetary factors. Removing it clarifies the policy-return relationship for the remaining events. The direction, sign, and significance of the main result are fully preserved under this robustness check.

For the MP subsample, excluding March 3, 2020 yields $\hat{\beta} = -11.67\%$ (SE $= 3.59\%$, $p = 0.004$, $N = 21$), again stronger than the corresponding full-sample MP estimate of -9.47%. This is consistent with the interpretation that the March 3 observation is atypical and that the pandemic emergency context contaminated the monetary policy signal.

Reclassification of the March 3, 2020 Event

In the baseline classification, March 3, 2020 is categorised as an accommodation event. An alternative classification treats it as a central bank information shock, given that the emergency cut conveyed substantial information about the Federal Reserve's assessment of pandemic severity rather than constituting a standard policy adjustment. Under this reclassification, the accommodation subsample expands to $N = 17$ and the coefficient is $\hat{\beta} = -3.95\%$ (SE $= 6.22\%$, $p = 0.535$), virtually identical to the baseline accommodation estimate of -3.92% ($p = 0.612$). The tightening subsample is unaffected, with $\hat{\beta} = -10.39\%$ (SE $= 3.60\%$, $p = 0.009$, $N = 23$) compared to the baseline -10.40% ($p = 0.008$, $N = 24$). Classification of this single event therefore has no material effect on either subgroup result, confirming that the conclusions are not artefacts of a boundary case.

Stability of the Tightening Subsample

Given that the tightening subgroup drives a substantial portion of the full-sample coefficient, it is important to verify that the tightening result is not itself driven by a small number of influential observations. Excluding March 3, 2020 from the tightening regression in the alternative classification yields $\hat{\beta} = -10.39\%$ (SE $= 3.60\%$, $p = 0.009$, $N = 23$), statistically and economically identical to the baseline tightening coefficient. The sensitivity of the tightening estimate to any single observation is therefore negligible.

Summary of Robustness Checks

Table 14 collects the full set of robustness estimates alongside the baseline. The overarching message is one of stability. Across all specifications, the sign of the coefficient is uniformly negative, the p-value remains below the five-percent threshold in every case, and the point estimate ranges from -8.40% to -11.67%. Far from being sensitive to the inclusion of any particular observation or classification boundary, the exclusion of the March 3, 2020 event consistently moves the coefficient in the direction of a stronger negative effect. The robustness of the tightening subgroup result is especially relevant given that tightening events dominate the sample, and it is reassuring that the estimate is essentially invariant to plausible alternative classifications of the single boundary case.

Table 14 – Robustness Checks: Event-Study Coefficient Across Alternative Samples and Classifications

Specification	N	$\hat{\beta}$ **(%)**	**HC3 SE**	$\boldsymbol{p}$**-value**
Baseline	40	−8.40	3.01	0.008
Excl. March 3, 2020	39	−10.73	3.97	0.010
Accommodation (original)	16	−3.92	7.56	0.612
Accommodation (reclassified)	17	−3.95	6.22	0.535
Tightening (original)	24	−10.40	3.58	0.008
Tightening (reclassified)	23	−10.39	3.60	0.009
MP subsample	22	−9.47	2.65	0.002
MP subsample, excl. March 3, 2020	21	−11.67	3.59	0.004

Notes: All regressions use HC3 heteroskedasticity-consistent standard errors following MacKinnon and White (1985). The dependent variable is the NASDAQ-100 same-day return on FOMC announcement days. The independent variable is the standardised high-frequency federal funds futures surprise (FF4). Accommodation (reclassified) and Tightening (reclassified) reassign the March 3, 2020 emergency meeting from the accommodation category to the central bank information shock category. MP subsample restricts to events classified as pure monetary policy shocks following Jarociński and Karadi (2020). Statistical significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Limitations

Several limitations of the present analysis warrant acknowledgement. First, the sample period of 2020–2024 yields forty FOMC announcement events. This figure represents the maximum available for the period under study: given that the FOMC convenes eight times per year, extending the sample to increase the event count would necessarily alter the research question by incorporating pre-COVID policy regimes that differ structurally from the period of interest. The constraint is therefore inherent to the design rather than a correctable shortcoming. While forty events is consistent with the event-study literature — Bernanke and Kuttner (2005) and Gürkaynak et al. (2005) work with samples of comparable size — the subgroup analyses necessarily involve smaller counts, which limits statistical power in the accommodation and CBI regressions in particular. An alternative design using firm-level panel data across the one hundred NASDAQ-100 constituents would expand the effective sample to approximately four thousand observations and permit an assessment of cross-sectional heterogeneity, but this lies beyond the scope of the present thesis. Second, the Campbell–Ammer decomposition relies on a VAR(1) estimated over a monthly frequency sample spanning 2001–2024. The log-linearisation constant ρ is calibrated to the sample mean dividend yield, which is very low for the NASDAQ-100; values of ρ close to unity can amplify small VAR coefficients and introduce numerical sensitivity into the news components. The results are reported for the preferred specification and were found to be directionally consistent across moderate variations in the variable set, but a systematic sensitivity analysis of the C-A parameterisation was beyond the scope of the thesis. Third, the LP-IV estimates lose precision rapidly beyond $h = 1$: of the 268 monthly observations used for estimation, only a relatively small number carry a substantial purified MP shock, and the effective instrument strength diminishes as the horizon lengthens. The widening confidence intervals at longer horizons should therefore be interpreted as reflecting sparse instrumentation rather than an absence of medium-term effects. Fourth, the classification of events into monetary policy shocks and central bank information shocks following Jaroćiński and Karadi (2020) relies on a sign-based algorithm applied to high-frequency changes in fed funds futures and Treasury yields; boundary cases exist, and the reclassification check in Section 5.4 addresses only one such case. Fifth, the NASDAQ-100 is a market-capitalisation-weighted index in which a small number of mega-capitalisation firms account for a disproportionate share of the total weight. Over the sample period, the ten largest constituents collectively represented more than fifty percent of index weight, with individual firms such as Apple, Microsoft, and Nvidia each carrying weights in excess of five percent. As a consequence, the estimated responses documented in this thesis may reflect primarily the monetary policy sensitivity of a handful of very large technology firms rather than the sensitivity of growth-oriented equities more broadly. Whether the findings generalise to smaller NASDAQ-100 constituents, or to growth-oriented firms outside the index, cannot be assessed from index-level data alone and constitutes a natural direction for future firm-level research.

5.5 Synthesis

Notwithstanding the limitations outlined above, the body of evidence assembled in this thesis is internally consistent and robust to the checks considered. The contractionary effect of a pure monetary policy shock on the NASDAQ-100 is consistently observed across multiple empirical frameworks used in this thesis. The event-study, LP-IV, and Campbell–Ammer results reinforce one another: all three point to a negative, statistically significant, and economically meaningful response, with the discount-rate and forward-guidance channels accounting for the identifiable portion of the transmission. The distinction between pure monetary shocks and central bank information shocks, which is a methodological contribution of the thesis relative to earlier event-study work, proves empirically consequential both for the sign and for the magnitude of the estimated response. These findings suggest that the identification discipline advocated by Miranda-Agrippino and Ricco (2021) and Jaroćiński and Karadi (2020) carries quantitative importance in equity-market applications, and that the transmission of U.S. monetary policy to growth-oriented equity segments is both large and structurally distinct from its transmission to the broad market. The implications for the theoretical understanding of the channels and for the generalisability of the findings to future policy cycles are taken up in Section 6.

6 Conclusion

This thesis examines the transmission of U.S. monetary policy shocks to the NASDAQ-100 over the 2020–2024 period, combining three complementary empirical exercises: a high-frequency event study, a Local Projections-IV framework, and a Campbell–Ammer return decomposition. The three exercises are unified by the identification discipline of Jaroćiński and Karadi (2020), whose sign-based separation of pure monetary policy shocks from central bank information shocks constitutes the methodological backbone of the analysis.

The empirical evidence, taken together, points to three main findings. First, pure contractionary monetary policy shocks generate a statistically significant and economically meaningful negative response in the NASDAQ-100 at the announcement horizon, with an estimated impact of -8.40% per one-standard-deviation surprise in the event study and -25.3% per one-percentage-point increase in the federal funds rate in the LP-IV framework. These two figures are not directly comparable in magnitude given differences in normalisation, sample frequency, and conditioning set, but they are directionally consistent and jointly indicate that identification discipline matters quantitatively: the raw futures surprise, which conflates a contractionary signal with a partially offsetting information component, yields an attenuated and statistically insignificant estimate of -10.2%. Second, the response is concentrated at short horizons, statistically robust at $h = 0$ and marginally significant at $h = 1$, which is consistent with the rapid informational repricing characteristic of a liquid institutional equity market. Third, the forward-guidance component of the policy surprise accounts for the dominant share of the NASDAQ-100 response, with the path factor coefficient of -12.63% statistically significant while the target factor is indistinguishable from zero, a result coherent with the unusually prominent role of dot-plot communication in the post-COVID monetary regime.

Regarding transmission channels, the Campbell–Ammer decomposition does not yield statistically significant evidence at the monthly frequency. None of the three news components, namely cash-flow news, discount-rate news, and equity risk premium news, achieves conventional significance in either the regression or the unconditional correlation analysis, so the channel attribution remains statistically inconclusive. This result does not imply that monetary policy has no effect through these channels; rather, it reflects the limited statistical power of monthly regressions to detect channel-specific effects when only a small fraction of observations carry a substantial purified MP shock. The absence of equity risk premium channel significance is nonetheless consistent with the H5 finding: once the central bank information component is purged from the raw surprise, the artefactual covariation that inflated equity risk premium responses in earlier unpurified studies is removed.

Two contributions follow from this evidence. First, the thesis provides one of the first applications of informationally robust shock identification to a sector-specific equity index, extending the aggregate macroeconomic applications of Miranda-Agrippino and Ricco (2021) and Jaroćiński and Karadi (2020) to a high-duration growth equity segment. Second, it documents that the identification discipline advocated by these authors carries quantitative importance in equity-market applications: the gap between the raw and purified LP-IV estimates directly confirms the H5 prediction that central bank information shocks partially offset the contractionary effect of pure monetary policy shocks. These findings are subject to the constraints of a forty-event high-frequency sample, which limits statistical power in subgroup analyses, and to the heavy concentration of the NASDAQ-100 in a small number of large-capitalisation technology firms, which means the estimated responses may not be representative of growth-oriented equities more broadly. Extending the analysis to the firm level and revisiting the channel decomposition with a longer sample when Greenbook-equivalent forecast data become available for the post-2020 period constitute natural directions for future research.

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