Macro-Equity Logic Chains in the Stock Market*

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Abstract

We study how equity analysts structure causal reasoning that links macroeconomic conditions to firm-level outcomes when forming forecasts. Using a comprehensive dataset that links each analyst to the full history of their macroeconomic and equity reports, we extract explicit causal statements describing how macroeconomic variables affect equity outcomes, which we term macro-equity logic chains or MELCs. We show that equity forecasts issued in reports containing MELCs are significantly more accurate, yet MELCs only appear in fewer than 10% of equity research. The components of MELCs, such as their types and length, are important in the improvement in forecast accuracy. Analysts' past exposure to MELCs through writing macro reports strongly predicts their subsequent use of similar reasoning in equity reports and is associated with improved forecast accuracy. Consistent with their greater informational content, the equity market responds more strongly to recommendations issued by analysts who more frequently employ MELCs.

Keywords: Macro-Equity Logic Chains, Experience, Analyst Forecast, Market Impact

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1 Introduction

Macroeconomic information is fundamental to equity valuation. Decades of research in finance show that macroeconomic news, such as monetary policy, economic growth, and commodity price movements, substantially affects aggregate equity returns and shapes both firm-level cash flows and discount rates. Macroeconomic content is also prevalent in the investment industry, consistently occupying the headlines of major financial news outlets. However, despite the prominence of macro news in the equity market, it remains unclear whether, and in what form, market participants explicitly relate macroeconomic content to the equity market in forming their forecasts. Traditional data sources, such as prices, trading activity, or surveyed expectations, reveal the outcomes of belief formation but not the underlying reasoning. As a result, we have limited evidence on the extent to which investors adopt macro-related chains of reasoning when evaluating equities and how such reasoning is shaped.

In this paper, we focus on analysts and directly examine their reasoning about how macroeconomic news and events affect equities. Leveraging an extensive corpus of reports from the *Investext* database—encompassing both equity research and macroeconomic analysis—we construct a complete writing history for each analyst. This dataset enables us to track their professional trajectories across various research departments and brokerage houses throughout their careers.

A key challenge we encounter is extracting macro-equity reasoning from the extensive and complex text data found in analyst reports. To address this, we leverage the chain-of-thought prompting strategy with Large Language Models (LLMs). Specifically, we construct a dataset that identifies the use of direct causal macro-equity reasoning in both macroeconomic and equity reports, which we refer to as *macro-equity logic chains* or MELCs. For example, in the equity report by Jonathan Chappell from J.P. Morgan, the analyst states: "Our overweight rating on KEX shares is based primarily on our belief that a continued recovery of the U.S. economy will result in a boost in petrochemical demand, thus improving the rates that Kirby earns on its barges and driving a return to double-digit EPS growth..." Using LLMs, we extract causal logic chains such as: *"Recovery of U.S. economy $\rightarrow$ double-digit EPS growth."* Such chains directly capture the reasoning employed by analysts to link macroeconomic events and variables to equities. By leveraging

MELCs, we gain a unique vantage point to observe the arguments underlying analysts' thought processes, revealing precisely which macro information they attend to and how it is incorporated into their equity forecasts.

To guide our empirical analysis, we develop a conceptual framework that models analysts as boundedly rational agents who face a trade-off between forecast precision and cognitive effort. In our model, analysts operate in a high-dimensional environment where processing complex causal links between macro signals and firm fundamentals—what we term the "Logic Chain Function"—imposes a cognitive cost. Consequently, analysts do not automatically process all available macro information. Instead, they make an endogenous adoption decision: they incorporate a specific macro-equity logic chain only if the reduction in forecast error variance (the value of insight) exceeds the cognitive burden of processing that chain. This framework generates sharp predictions regarding the rarity of these logic chains, the conditions under which they improve accuracy, and how the accumulation of experience lowers cognitive costs, thereby facilitating the adoption of macro reasoning.

We begin our empirical analysis by studying the properties of analysts' MELCs through the lens of this framework. First, we present a fact that MELCs only appear in a relatively small number of equity reports, despite the importance and prevalence of macroeconomic news in driving the equity market. While approximately 20% of reports contain macroeconomic keywords, fewer than half of those explicitly articulate a causal chain. Consequently, the unconditional probability of observing a MELC is only 8%. This sparsity aligns with our framework's prediction that when the base cognitive cost of macro reasoning is high relative to the perceived benefit for a specific firm, the equilibrium adoption rate will be low. Strikingly, even during the onset of the 2008 Great Financial Crisis, only about 13% of the equity reports contain any MELC, suggesting that the cognitive hurdle for explicit macro reasoning remains significant even during periods of high macro salience.

One potential explanation for the scarcity of MELCs that does not base on cognitive costs is that analysts incorporate macroeconomic information implicitly, without explicit articulation. However, our findings suggest otherwise. In particular, our framework implies that if an analyst incurs the cognitive cost to explicitly reason through a logic chain, this effort should result in a measurable improvement in

precision. Consistent with this prediction, we find that equity forecasts accompanying reports with MELCs are significantly more accurate than those without. These results are robust to the inclusion of analyst, firm, and year fixed effects, indicating that time-invariant characteristics do not drive the findings. Furthermore, the relationship between forecast accuracy and MELCs holds even after controlling for the mere presence of macroeconomic keywords. This suggests that MELCs capture specific, value-relevant reasoning rather than general attention to macroeconomic news, consistent with the prediction of the conceptual model.

We next examine the specific components of MELCs to validate the underlying mechanism of our model. Our framework posits that analysts exhibit 'selective attention,' prioritizing logic chains to which a firm is most sensitive. We test this by categorizing MELCs into three domains: Commodity & Materials, Domestic Economy, and Monetary Policy. We find that analysts indeed tailor their adoption of MELCs to the firm's exposure profile—for instance, utilizing more commodity logic chains for firms with high commodity betas. Crucially, MELCs improve forecast accuracy most significantly when they match the firm's specific macro exposure – e.g., commodity logic chains significantly benefit forecasts for firms with high commodity betas. This evidence supports the view that analysts engage in a rational selection process, adopting logic chains that align with the firm's fundamental drivers. Additionally, while both short and long MELCs improve accuracy, the effects are more pronounced for shorter chains, suggesting they capture the most salient causal signals with a lower risk of model misspecification.

Next, we examine the drivers of MELC usage, with a particular focus on the role of experience. Our conceptual framework posits that cognitive costs are not static; rather, they decline as analysts accumulate domain familiarity—a mechanism supported by cognitive psychology research on schema formation and dual-process cognition. We begin with a variance decomposition analysis, which reveals that analyst-firm fixed effects explain a substantial share ($\sim$30%) of the variation in MELC usage.[1] The large role of analyst-firm fixed effects is in line with stable pair-specific differences in relevance and cognitive cost as emphasized in our conceptual framework. Additionally, we find that this usage is highly persistent, underscoring the 'stickiness' of macro-equity reasoning. Standard analyst demographics and firm characteristics have little explanatory power, prompting us to look at the analyst's specific history of reasoning.

[1]This aligns with Giglio et al. (2021) and Kwan et al. (2025).

Leveraging our ability to link analysts to their complete history of macroeconomic and equity research, we test the model's prediction that experience lowers the marginal cost of adoption. We document that analysts tend to employ similar types of MELCs across their macro and equity reports. Specifically, we find that having recent experience writing macro reports with MELCs is associated with a 0.8% higher probability of including a similar logic chain in subsequent equity reports—a sizable effect given the low baseline usage rate. Dynamic analysis shows no pre-trend differences between treatment and control groups, supporting a causal interpretation. Furthermore, forecast errors decrease significantly subsequent to these experiences. This evidence supports our framework's mechanism: past experience in macro reporting lowers the cognitive cost of macro-equity reasoning, inducing analysts to apply this logic in equity valuation, which in turn improves forecast accuracy.

Moreover, we show that this experience effect is domain-specific. Analysts' past experiences with a specific MELC type in macro reports lead to an increase in the usage of that same MELC type in equity evaluation, rather than a general increase in all logic chains. To sharpen identification, we employ an instrumental variable (IV) approach using the past experience of the analyst's team lead, reaching similar results.

Having established that MELCs improve forecast accuracy and are driven by experience, we turn to their broader economic consequences: does the market recognize the value of this reasoning? We investigate whether investors respond differentially to recommendation revisions issued by analysts who frequently employ MELCs. Using both panel regressions and non-parametric portfolio sorting, we document a strong positive relationship between an analyst's historical propensity to use MELCs and the immediate market reaction to their recommendation changes. Specifically, a one-standard-deviation increase in an analyst's historical MELC usage is associated with a 10.8 basis point increase in the immediate signed cumulative abnormal return (CAR) following a revision. Similarly, a long-short portfolio strategy based on MELC usage yields an abnormal return of approximately 25 basis points around the revision window. These findings indicate that market participants distinguish between analysts based on their reasoning styles, attributing greater informational value to those who explicitly articulate macro-equity logic.

Lastly, we conduct a number of additional tests and robustness checks. First, we show that our baseline

results are quantitatively similar across different valuation methods employed by the analysts as defined in Bastianello et al. (2024), suggesting that the effect of MELCs permeates all valuation approaches emphasized in the literature. Second, consistent with our model where high-cost agents benefit most from experience-driven cost reductions, the effect of past experiences is stronger among non-lead analysts—those face high cognitive cost and less likely to endogenously employ MELCs.[2] Third, we find qualitatively similar results when restricting the analysis to analysts with limited macro writing experience or to periods of high economic uncertainty (Baker et al. 2016), where the decision to write macro reports is likely more exogenous. Fourth, we confirm our main analyses using stacked difference-in-difference (DiD) estimation methods. Finally, we show that the market impact results are robust to various alternative specifications.

Literature Review. Our paper relates to several streams of literature. To begin with, we contribute to the literature on the studies of economic reasoning and arguments in financial markets. Economic reasoning and arguments can also be considered as fundamental building blocks of mental models. It has been proposed that mental models—agents' mental representations of how the economy and markets work—can explain a variety of puzzling phenomena in economics and finance, including financial decisions (e.g., Andre et al. 2022; Andre et al. 2024; Andre et al. 2025; Barron and Fries 2024; Charles and Kendall 2024), taxation (e.g., Stantcheva 2021), and macroeconomics (e.g., Stantcheva 2022). Kendall and Oprea (2024) conduct experiments showing that it is challenging for agents to form predictive models of even simple data-generating processes. Most of the existing evidence is experimental. An important exception is recent papers by Bastianello et al. (2024) and Ke (2024). Using equity reports, the former examines a specific type of mental model used by analysts—the interaction between attention and valuation method (e.g., discounted cash flow, multiples-based, etc.), and the latter studies the factual and subjective components of report content in the formation of analysts' subjective beliefs.

Our study differs from the existing literature in several key ways. First, we provide field evidence about the properties and importance of reasoning and argument in the financial markets. In particular, we focus on analysts' reasoning and arguments that link macro events to equity evaluation. Second, we show that the

[2]This pattern implies that our baseline estimate may represent a lower bound, as the use of such logic appears to be a persistent trait among those who self-select into writing macro reports.

reasoning and arguments have material effects and significantly affect analysts' forecast errors. Third, we shed light on the drivers of the reasoning and arguments by connecting analysts' past experiences to their macro-equity reasoning in equity reports.

The paper relates to the literature of experiences. Malmendier and Nagel (2011) and Malmendier and Nagel (2016) show that the importance of early life experiences of certain macroeconomic events significantly affects agents' economic attitudes later in life. Other papers show the importance of experiences in various settings, such as inflation expectations (e.g., D'Acunto et al. 2021), stock investments (e.g., Greenwood and Nagel 2009; Kaustia and Knüpfer 2008; Knüpfer et al. 2017), and management styles (e.g., Schoar and Zuo 2017). Our paper contributes to this literature by showing that past experiences of macro-equity reasoning can lead to similar macro-equity reasoning in evaluating equities.

Lastly, the paper also relates to the literature on expectation formation. Various mechanisms have been proposed to account for expectation formation, such as information-based (e.g., Mankiw and Reis 2002; Van Nieuwerburgh and Veldkamp 2009, 2010), extrapolation (e.g., Barberis et al. 2015; Barberis et al. 2018; Jin and Sui 2022; Da et al. 2021), memory (e.g., Charles 2022, 2024; Charles and Sui 2024; Jiang et al. 2025), narratives (e.g., Shiller 2020; Kendall and Charles 2022), and structured beliefs (e.g., Gao et al. 2025). Our results on forecast errors show that macro-equity reasoning helps analysts form more accurate beliefs of equity performances.

The rest of the paper is organized as follows. Section 3 discusses the background and the data used in this paper. Section 4 studies the properties of analysts' macro-equity reasoning in evaluating equities, and Section 5 examines the relationship between MELCs and forecast accuracy. Section 6 examines the drivers of MELCs. Section 7 studies the differential market impact by recommendations made by analysts who tend to use MELCs. Section 8 conducts additional tests. Finally, Section 9 concludes the paper.

2 A Conceptual Framework

This section presents the conceptual framework that guides our study. We model analysts as information processors who must determine not only *whether* to process macro information, but *which* specific macro-

equity logic chains to incorporate into their valuation.

We proceed in three steps. First, we define the information environment and the asset valuation structure, introducing a recursive, multi-layered transmission mechanism for macro signals. Second, we define the analyst's technology and cognitive cost function. Third, we derive the equilibrium adoption strategy, where analysts select logic chains based on a trade-off between accuracy and cognitive effort.

2.1 The Environment

At time t, a universe of Q unique macroeconomic signals, denoted by $m_t \in \mathbb{R}^Q$, is publicly available to the analyst i. These signals include indicators such as inflation, monetary policy, commodities, and GDP growth. Given that distinct macro-equity logic chains rely on specific categories of macro information, we organize these signals into K semantic groups.

Let $m_t^{(k)} \in \mathbb{R}^{q_k}$ represent the vector of signals corresponding to the k-th group. Since a single macro variable may be relevant to multiple logic chains, these groups are allowed to overlap. Consequently, the cumulative dimension of the groups satisfies:

$$\sum_{k=1}^{K} q_k \geq Q.$$

Let y_t denote a target outcome for the firm (e.g., earnings, valuation), which is driven by the interplay of idiosyncratic micro-fundamentals and a set of macro-economic factors. We model the true macro-economic factor $F_{k,t}$ as the outcome of a multi-layered logic chain. A logic chain k consists of $S_k \geq 1$ sequential reasoning layers (e.g., A affects B, B affects C, and so on).

As we reason through each layer of the logic chain, the logical deductions may not perfectly match actual real-world dynamics. Consequently, a layer-specific noise component is injected at every step of the process. Therefore, we define the true state of the reasoning chain at layer s as $x_{k,s}$, governed by the recursive relationship:

$$x_{k,0} = m_t^{(k)}$$

$$x_{k,s} = g_{k,s}(x_{k,s-1}) + \eta_{k,s} \quad \text{for } s = 1, \ldots, S_k$$

where $g_{k,s}(\cdot)$ represents the deterministic transmission function (of our logic chains) at layer s, and $\eta_{k,s} \sim N(0, \sigma_\eta^2)$ represents the exogenous structural noise introduced *inside* that specific layer. The true factor realization is the output of the final layer: $F_{k,t} = x_{k,S_k}$. For analytical tractability, we assume the transmission functions $g_{k,s}$ are variance-preserving linear mappings.

Let $\mathcal{L}_k(m_t^{(k)})$ represent the purely deterministic, theoretical reasoning path for logic chain k. Formally, it is defined as the sequential composition of all transmission functions $g_{k,s}$ evaluated at the initial macro signal:

$$\mathcal{L}_k(m_t^{(k)}) = (g_{k,S_k} \circ g_{k,S_k-1} \circ \cdots \circ g_{k,1})(m_t^{(k)})$$

Because structural noise is injected sequentially at each layer, it compounds throughout the reasoning process. Consequently, the total accumulated reasoning noise for logic chain k has a variance of $S_k\sigma_\eta^2$.

The data-generating process for the asset value is therefore given by:

$$y_t = \mu + \sum_{k=1}^{K} \beta_k \cdot F_{k,t} + \epsilon$$

The model distinguishes between firm-specific shocks and systematic macro drivers. The term $\mu \sim N(0, \sigma_\mu^2)$ represents the idiosyncratic micro-component. The parameter β_k captures the firm's specific sensitivity to the k-th macro factor. We assume the deterministic logic chains are mutually orthogonal, such that $Cov(\mathcal{L}_j, \mathcal{L}_k) = 0$ for all $j \neq k$. To isolate the effect of chain length, we assume the total variance of each true macro factor $F_{k,t}$ is a constant V_F. Consequently, the explainable variance provided by the deterministic logic chain is $\sigma_{L_k}^2 = V_F - S_k\sigma_\eta^2$, which strictly decreases as the chain length S_k increases. Finally, the system is subject to an exogenous noise term, $\epsilon \sim N(0, \sigma_\epsilon^2)$.

2.2 The Analyst's Adoption Decision

We model the analyst as a boundedly rational agent subject to cognitive burdens. In a high-dimensional environment, analysts cannot process the full spectrum of macroeconomic data. Instead, they endogenously curate their information set by selecting specific logic chains to adopt.

We capture this selection process using a vector of binary decision variables, $D_i = \{d_{i,1}, d_{i,2}, \ldots, d_{i,K}\}$, where $d_{i,k} \in \{0, 1\}$. When $d_{i,k} = 0$, the analyst relies on a heuristic simplification, ignoring the k-th macro

mechanism. Conversely, $d_{i,k} = 1$ indicates a logical process wherein the analyst expends the mental labor to decode the deterministic transmission mechanism $\mathcal{L}_k(m_t^{(k)})$. Consequently, the analyst i's forecast at time t, $\hat{y}_{i,t}$, is a composite of a baseline micro-view and a selected subset of macro-insights:

$$\hat{y}_{i,t} = \mu + \sum_{k=1}^{K} d_{i,k} \cdot \beta_k \cdot \mathcal{L}_k(m_t^{(k)})$$

2.3 Cognitive Cost and Learning

Adopting these logic chains imposes a significant cognitive burden. We capture the internalization of reasoning by defining the total *Cognitive Cost* function, $C_i(D_i)$, as:

$$C_i(D_i) = \sum_{k=1}^{K} d_{i,k} \cdot c_{i,k}, \quad \text{where } c_{i,k} = \kappa \cdot S_k \cdot e^{-\lambda E_i}$$

In this framework, $\kappa > 0$ represents the *base cognitive cost* per reasoning layer. The total cost of a logic chain scales linearly with its length S_k. Let $E_i \geq 0$ denote the analyst's accumulated stock of experience. The term $e^{-\lambda E_i}$ models the impact of this experience on cognitive cost, where $\lambda > 0$ governs the rate of learning.

2.4 Optimization and Equilibrium Implications

The analyst's objective is to choose the vector D_i that minimizes the Total Loss Function, defined as the sum of the expected squared forecast error (MSE) and the total cognitive cost:

$$\min_{\{d_{i,k}\}_{k=1}^{K}} \quad \mathbb{E}\left[(y_t - \hat{y}_{i,t})^2\right] + \sum_{k=1}^{K} d_{i,k} c_{i,k}$$

The assumption of orthogonality among logic chains ensures that this optimization problem is separable. We now derive the following propositions that underpin our empirical findings.

Proposition 1 (Rarity of Adoption). *An analyst adopts a specific logic chain k (sets $d_{i,k} = 1$) if and only if the reduction in forecast error variance provided by that chain exceeds its marginal cognitive cost.*

Proof. The Mean Squared Error (MSE) can be decomposed based on the included and excluded chains. Because the true factor $F_{k,t}$ contains compounded internal noise that the deterministic forecast $\mathcal{L}_k(m_t^{(k)})$ cannot capture, the error term is:

$$y_t - \hat{y}_{i,t} = \sum_{k=1}^{K}(1 - d_{i,k})\beta_k \mathcal{L}_k(m_t^{(k)}) + \sum_{k=1}^{K}\beta_k(F_{k,t} - \mathcal{L}_k(m_t^{(k)})) + \epsilon.$$

Taking the expectation of the square, and utilizing the orthogonality of $\mathcal{L}_k$ and the independence of the compounded layer noise:

$$MSE(D_i) = \sum_{k=1}^{K}(1 - d_{i,k})\beta_k^2\sigma_{L_k}^2 + \sum_{k=1}^{K}\beta_k^2 S_k\sigma_\eta^2 + \sigma_\epsilon^2$$

The analyst adopts chain k if the cost of inclusion is less than the penalty of exclusion (the variance reduction). Thus, $d_{i,k} = 1$ if and only if:

$$\underbrace{\beta_k^2\sigma_{L_k}^2}_{\text{Value of Insight}} > \underbrace{\kappa S_k e^{-\lambda E_i}}_{\text{Cognitive Cost}}$$

□

Proposition 2 (The Chain Length Effect on Adoption). *Logic chains with longer lengths (S_k) are strictly less likely to be adopted, ceteris paribus.*

Proof. Recall that the explainable variance of the deterministic chain is $\sigma_{L_k}^2 = V_F - S_k\sigma_\eta^2$. As chain length S_k increases, the Value of Insight ($\beta_k^2(V_F - S_k\sigma_\eta^2)$) decreases due to the compounding internal noise, while the Cognitive Cost ($\kappa S_k e^{-\lambda E_i}$) increases. Therefore, the adoption condition in Proposition 1 becomes strictly harder to satisfy for longer chains. □

Proposition 3 (Selective Attention). *Analysts will exhibit selective attention, prioritizing logic chains with high firm-sensitivity (β_k) or short reasoning paths (S_k), while ignoring those with low explanatory power or high complexity.*

Proof. This follows from the inequality in Proposition 1 and the derivation in Proposition 2. For a fixed level of experience E_i, the analyst will only adopt the subset of chains where the benefit $\beta_k^2(V_F - S_k\sigma_\eta^2)$ is sufficiently large to overcome the cost threshold $\kappa S_k e^{-\lambda E_i}$. □

Proposition 4 (The Accuracy Premium). *The expected forecast error is strictly decreasing in the number of relevant logic chains adopted.*

Proof. Recall the MSE decomposition derived in Proposition 1. When an analyst switches the decision variable $d_{i,k}$ from 0 to 1 for a relevant chain (where $\beta_k \neq 0$), the positive variance term $\beta_k^2 \sigma_{L_k}^2$ is eliminated from the error sum. While the unobservable compounded layer noise $S_k \sigma_\eta^2$ remains, analysts who process a wider range of relevant logic chains structurally exhibit lower forecast errors. □

Proposition 5 (The Relevance Effect on Accuracy). *The reduction in forecast error gained from adoption is strictly increasing in the firm's sensitivity to that specific logic chain.*

Proof. The reduction in MSE conditional on adopting chain k is exactly $\Delta\text{MSE}_k = \beta_k^2 \sigma_{L_k}^2$. Taking the partial derivative with respect to the magnitude of sensitivity $|\beta_k|$, we obtain:

$$\frac{\partial(\Delta\text{MSE}_k)}{\partial|\beta_k|} = 2|\beta_k|\sigma_{L_k}^2 > 0$$

Thus, the accuracy gain is most pronounced for logic chains where the firm has a high factor loading (β_k). □

Proposition 6 (Attenuation of Accuracy Gains). *For any adopted logic chain, the magnitude of the increase in forecast accuracy strictly declines as the length of the logic chain (S_k) increases.*

Proof. Let the accuracy gain from adopting chain k be defined as the reduction in Mean Squared Error:

$$\Delta\text{MSE}_k = \text{MSE}(d_{i,k} = 0) - \text{MSE}(d_{i,k} = 1) = \beta_k^2 \sigma_{L_k}^2$$

Substituting the explainable variance $\sigma_{L_k}^2 = V_F - S_k \sigma_\eta^2$, the accuracy gain is:

$$\Delta\text{MSE}_k = \beta_k^2 (V_F - S_k \sigma_\eta^2)$$

Taking the partial derivative of this accuracy gain with respect to chain length S_k, we obtain:

$$\frac{\partial(\Delta\text{MSE}_k)}{\partial S_k} = -\beta_k^2 \sigma_\eta^2 < 0$$

Because structural noise $\eta_{k,s}$ is injected recursively inside the multi-layer function $\mathcal{L}_k$, it compounds with each additional reasoning step. Consequently, the extractable deterministic signal weakens. This implies that successfully processing a longer logic chain yields a structurally smaller increase in forecast accuracy compared to processing a shorter chain with the identical factor sensitivity. □

Proposition 7 (The Experience Effect). *The number of logic chains adopted by an analyst is non-decreasing in Experience E_i.*

Proof. Let $f(E_i) = \kappa S_k e^{-\lambda E_i}$ be the cognitive cost function. Since $f'(E_i) = -\lambda\kappa S_k e^{-\lambda E_i} < 0$, the marginal cost for *every* chain k decreases as experience increases. Consequently, chains that were previously too costly to process may now satisfy the adoption condition. Thus, more experienced analysts incorporate a broader scope of macro-equity logic into their forecasts. □

3 Data and Methodology

This section constructs the key objects of the paper: macro-equity logic chains and analysts' adoption of those chains in written research. To investigate the properties of analysts' macro-equity reasoning, we exploit a comprehensive dataset of equity research reports that tracks analysts' publication histories over decades. We begin by outlining the data sources and the construction of this sample. We then define the concept of *logic chains* in the context of financial analysis. Finally, we detail our methodology for systematically extracting these reasoning patterns from the unstructured report text using Large Language Models (LLMs).

3.1 Analyst Equity Reports

We construct our sample of analyst equity reports using the Investext database, a comprehensive global aggregator of analyst research accessible via Mergent Online. This platform hosts a vast repository of equity reports produced by professional sell-side analysts. These documents serve a diverse clientele of institutional and individual investors seeking expert insights into specific firms, industries, or the broader economy. Our dataset spans the period from January 1, 1998, through December 31, 2024, and encompasses reports from prominent brokerage houses and investment banks such as J.P. Morgan, Credit Suisse, and Deutsche Bank Securities. Within this institutional setting, reports are authored by either individual analysts or collaborative teams. As noted by Gao et al. (2021), the author order typically signifies relative contribution; therefore, the lead analyst is generally considered responsible for the primary qualitative content.

To prepare the data for textual analysis, we first download the full PDF versions of all relevant reports

published during our sample period. We then convert these documents into plain text using MinerU, an open-source algorithm specialized in PDF document processing.[3] Following this initial conversion, we implement a rigorous cleaning procedure to remove non-narrative elements, such as standardized regulatory boilerplate, figures, and tables. The goal of this processing pipeline is to isolate a clean, unstructured textual segment that focuses exclusively on the analysts' narrative reasoning and recommendations. The resulting sample contains 5,330,751 equity reports by 35,302 distinct equity analysts.

Beyond the documents themselves, Investext provides extensive metadata. This enables us to observe granular features such as release dates, titles, and author names, as well as internal classifications for report style and subject. For reports covering individual stocks, we also observe company identifiers, including names and tickers. These features allow us to match reports to the corresponding securities and analyst identities, as well as to their forecast records in the IBES database. Additional details regarding the dataset construction and matching procedures are provided in Appendix A.

The matching procedure yields a final sample of 4,437,420 equity reports authored by 9,756 IBES-matched analysts covering U.S. firms. Approximately 1.1 million forecasts are matched to the analyst equity reports. Panel A of Table 4 presents summary statistics for our sample of equity reports written by IBES-matched analysts. On average, a report is produced by 1.8 analysts and has a total length of 1,125 words. Among analysts who authored at least one equity report, the majority are male (75.3%) and white (70.4%). The average equity analyst in our sample has a tenure of 6.3 years, during which they write a report approximately once every 25 days and issue an earnings forecast once every 40 days.

3.2 Macro-Equity Logic Chains

The primary function of equity reports is to provide insight into a firm's earnings performance and valuation. Indeed, equity analysts typically use these reports to detail a firm's recent earnings, generate financial forecasts, and outline potential risks to their outlook. For illustration, Figure A1 presents an equity report from J.P. Morgan. In this document, analysts review recent sales and earnings performance,

[3]MinerU converts PDF content to structured markdown format. Its key advantage lies in accurately distinguishing tabular data from narrative text and preserving the original paragraph structure during extraction, which is crucial for subsequent textual analysis.

issue a "Neutral" recommendation, and justify their stance by citing weak demand and concerns regarding accounting transparency.

To understand how stock investors integrate macroeconomic information into their equity valuations, we examine macro-equity logic chains (MELCs) reflected in the analyst equity reports. We define MELCs as the specific causal links analysts draw between macroeconomic variables and equity outcomes. For instance, the statement "rising GDP leads to higher earnings" serves as a vivid example of how, in the analyst's perception, macroeconomic factors influence firm fundamentals.

Conceptually, we focus on MELCs because these logic chains are the fundamental constituents of human decision-making. They serve as the building blocks of mental models—a concept that has gained significant traction in recent economic and financial research. While mental models represent the broader cognitive frameworks investors use to interpret the world, MELCs are the specific logic chains that construct these frameworks. For example, the MELC above—"rising GDP leads to higher earnings"—could serve as one of the key components in a mental model that interprets the functioning of the economy and the stock market. Consequently, by analyzing MELCs, we can better decode the internal architecture of these complex models, gaining a more granular understanding of the mechanisms driving belief formation and market behavior.

3.3 Extract MELCs using LLMs

We use Large Language Models (LLMs) to systematically extract MELCs from our corpus of equity reports. Figure 1 illustrates the workflow of our extraction process. LLMs are particularly well-suited for this objective due to their capacity to identify abstract concepts and distill complex reasoning patterns from unstructured text (Li et al. (2024)). Specifically, we utilize the 'DeepSeek-V3.2-Exp' model. Its architecture, which is optimized for efficient long-context processing, enables us to preserve the integrity of extended logic chains while simultaneously minimizing computational costs.

To optimize the extraction process, we implement a targeted retrieval approach. For each report, we first locate key sentences containing macroeconomic information based on the keyword list from Fisher et al. (2022) (e.g., "GDP," "unemployment," and "monetary policy"). We then isolate these key sentences along with their immediately preceding and succeeding context to serve as the input for the LLM.

To ensure extraction accuracy, we design a prompt featuring a structured "Chain-of-Thought" procedure. This approach decomposes the complex task into sequential steps, improving both model performance and interpretability. First, we instruct the LLM to identify logic chains (A $\rightarrow$ B) signaled by explicit causal expressions such as "because", "due to", and "therefore". Second, for each extracted chain, the model determines whether it contains elements associated with macroeconomic variables and equity concepts. Panel A of Table 1 provides the full prompt. Throughout our analysis, we set the temperature parameter to zero and restrict the model to extracting explicit rather than inferred causal relations. These settings minimize variation and effectively hinder the hallucination of content not present in the reports. Collectively, this procedure significantly enhances both the efficiency and precision of our macro-equity logic extraction.

This approach effectively captures MELCs within analyst reports. To illustrate, consider an excerpt from an equity report by David Wong of Wells Fargo:

> *"On September 28, DigiTimes reported that market sources expected TSMC's sales to grow 10% or more for Q3 2012 before falling 10% or more in Q4 2012 ... However, In the December quarter, TSMC expects a decline in revenue, based off of a deterioration in the global economic outlook over the past 3-6 months."*

The LLM processes this text and extracts the chain *"deterioration in global economic outlook $\rightarrow$ expected decline in revenue."* This example confirms that LLMs can accurately detect and extract the causal relationships between macroeconomic variables and equity variables. A more comprehensive set of illustrative examples is provided in Table 2.

Notably, the extracted MELCs can potentially contain chains spanning more than two layers. Logic chains capturing sequences such as (A $\rightarrow$B $\rightarrow$ C) or (A $\rightarrow$B $\rightarrow$ C $\rightarrow$ D) are entirely plausible and, in fact, account for 25% of the extracted MELCs in our sample. To facilitate our analysis, we decompose these longer chains by focusing exclusively on the cause and the outcome—the first and last elements of the chain. We discuss additional properties of these extended logic chains in Section 5.2.2.

3.4 Using LLMs to Classify MELCs

Following the extraction of MELCs from equity reports, we employ LLMs to further classify their causes and outcomes. For causes, we adopt a two-step classification process. First, following Fisher et al. (2022), we prompt the LLM to assign each cause to one of eight predefined categories: Commodity, GDP, U.S. Dollar, Inflation, Monetary, Housing Market, Unemployment, and Credit Rating. Causes that do not fit these descriptions are labeled "Other." In the second step, we aggregate these eight categories into three broader classifications: "Commodity & Materials," "Domestic Economy," and "Monetary Policy." Panel A of Table 3 details this classification process.

We apply a similar two-step procedure for equity outcomes. First, using a random sample of 4,000 logic chains, we leverage LLMs to classify them into nine distinct categories: Stock Valuation, Market Valuation, Earnings & Profitability, Revenue & Sales, Financial Strategy, Production & Costs, Market & Competition, and Demand & End-Market. We then consolidate these nine categories into three broader classifications: "Equity Valuation," "Earnings & Revenue," and "Business Operations." Detailed descriptions are provided in Panel B of Table 3.

Finally, by intersecting the three broad classifications for causes with those for outcomes, we identify nine distinct types of MELCs. Detailed descriptions of these logic chains are presented in Panel C of Table 3.

3.5 Validation

In this subsection, we conduct a number of validation tests for the MELCs extracted using the "DeepSeek-V3.2-Exp" model. We compare the performance of "DeepSeek-V3.2-Exp" against human annotations of a randomly chosen set of 100 MELC-related segments (50 from equity reports and 50 from macro reports). We use the same evaluation metrics as Li et al. (2021) to assess the accuracy for the MELCs extracted using the 'DeepSeek-V3.2-Exp' model. We refer readers to Li et al. (2021) for the detailed definitions of the evaluation metrics.

Table A1 in the Appendix summarizes model performance. For the report-level task of identifying whether a report contains any MELC, the model achieves a high accuracy benchmarked on human annota-

tions, as shown in panel A. The accuracy is about 90% in equity reports and about 98% in macro reports based on various evaluation metrics in both samples. For cause and outcome categorization, performance remains highly accurate. The joint cause-outcome type is the most demanding task and still exhibits high accuracy with more than 70% accuracy for both equity and macro. For robustness, we report model performance for "Gemini-2.5-Flash" in Panel B and show that the two models perform similarly in extracting logic chains. Overall, the validation indicates that the LLM pipeline reliably identifies explicit macro-equity causal reasoning and assigns the broad categories used in our main analysis.

3.6 Other Data Sources

Beyond equity reports, a distinct advantage of our sample is the inclusion of a comprehensive set of macroeconomic reports. Classified by Investext as either "Commodity" or "Economic," these documents analyze macroeconomic conditions at both national and global levels. In these reports, analysts offer insights into current and future economic trends—covering topics such as GDP, inflation, and monetary policy—and evaluate the impact of these factors on equity markets. Consistent with our equity report data, we possess extensive metadata that enables us to link these documents to specific analyst identities. Similarly, we extract and classify MELCs from these macroeconomic reports using the prompts detailed in Tables 1 and 3.

Additionally, to supplement these textual sources, we gather stock returns from CRSP and financial indicators from Compustat. Panel B of Table 4 presents the statistics for the matched earnings forecast sample. The mean absolute forecast error is approximately seven times the standard deviation of the past consensus error. On average, the sample firms are 12.7 years old and have a market capitalization of $3 billion. The typical firm has a book-to-market ratio of 0.6 and a profitability rate of 9%.

4 Properties of Macro-Equity Reasoning in Evaluating Equities

In this section, we begin with the conceptual framework's descriptive implications by asking what MELCs look like in the data and how frequently analysts adopt them in the context of equity evaluation. We begin by outlining what these MELCs look like. Next, we show that analysts use them in a relatively small

number of equity reports, consistent with the view that MELCs are structured but selectively adopted with significant cognitive costs. Finally, we demonstrate that adopting these logic chains significantly improves forecast accuracy.

4.1 Visualization of Macro-Equity Logic Chains

We first examine the landscape of MELCs extracted from equity reports. The Sankey diagram in Panel A of Figure 2 visualizes the distribution of these logic chains. The source bars on the left—representing the "Causes"—are ordered from top to bottom as Commodity & Materials, Domestic Economy, and Monetary Policy. These flow into the "Outcome" bars on the right: Equity Valuation, Earnings & Revenue, and Business Operations. The height of each bar corresponds to the total number of relevant logic chains, while the width of the flows is proportional to the frequency of specific cause-and-effect pairings. Subcategories belonging to the same broader classification are grouped together; for instance, GDP, Unemployment, and the Housing Market are all clustered within the "Domestic Economy" classification.

Several salient features stand out. First, the dominant causal category among macroeconomic variables is "Commodity." This is unsurprising given the significant impact of commodity prices on raw material costs—a critical driver of firms' cost structures and operational activities. Another prominent cause is GDP, which reflects aggregate economic demand and plays a pivotal role in determining firm revenue and earnings. Similarly, monetary policy is a frequently discussed macroeconomic driver, as it significantly influences financing costs, thereby affecting both revenue and valuations.

Second, the primary equity outcome categories are stock valuation, market valuation, and earnings & profitability. These outcomes are inherently sensitive to macroeconomic conditions. For example, firm earnings react strongly to shifts in macroeconomic variables. Furthermore, these specific outcomes attract substantial attention from market participants due to their centrality in investment decision-making.

Third, across the different types of MELCs, the most frequently cited chains involve commodities influencing Stock Valuation and Earnings & Profitability. We also observe a notable volume of chains linking GDP to market valuation, and Monetary Policy to both Earnings & Profitability and Stock Valuation. Additionally, currency shocks carry significant weight as a causal factor, emphasizing the link between the

U.S. Dollar and both stock valuation and Earnings & Profitability.

Finally, it is important to note that this Sankey diagram presents a *conditional* landscape, visualizing only the valid extracted MELCs. Unconditionally, the fraction of equity reports containing MELCs is relatively low; we address this scarcity in Section 4.3.

4.2 Keywords in Macro-Equity Logic Chains

In this section, we examine the textual content of the specific components that constitute these logic chains. Figure 3 presents word clouds corresponding to the three categories of macroeconomic causes and the three categories of equity outcomes defined in Table 3.

The visualization reveals striking lexical distinctions across the panels. Among macroeconomic causes, the Commodity & Materials cloud is dominated by tangible input terms like "Oil" and "Natural Gas," reflecting direct cost and revenue drivers. In contrast, Domestic Economy centers on aggregate health indicators such as "GDP," "Housing," and "Unemployment," while Monetary Policy is characterized by financial levers like "Rate," "Fed," and "Dollar." A similar specificity appears in the equity outcomes: Equity Valuation prioritizes market terminology ("Price Target," "Valuation"); Earnings & Revenue anchors on accounting metrics ("EPS," "Earning"); and Business Operations emphasizes functional impacts ("Demand," "Risk," "Sector").

Notably, there is minimal semantic overlap between these categories. This lexical distinctness indicates that analysts adopt highly structured and diverse Macro-Equity Logic Chains (MELCs), utilizing precise vocabulary for specific contexts rather than generic economic narratives. Furthermore, the clear separation of terms confirms that the LLM successfully distinguishes between nuanced types of macroeconomic causes and equity outcomes.

Additionally, the prominence of terms within these word clouds reflects the distributional patterns shown in Figure 3. The dominance of specific keywords aligns with the high-frequency categories identified in our earlier distribution analysis, reinforcing the internal consistency of the extracted data. For example, among the logic chains where monetary policy is identified as the macroeconomic cause, the Sankey diagram in Figure 2 highlights the dominance of the U.S. Dollar and Monetary Policy subcategories. This observation

is further supported by the word cloud, where terms such as "U.S. Dollar" (linked to the U.S. Dollar subcategory) and "Interest Rate" and "Federal Reserve" (corresponding to the Monetary Policy subcategory) appear with high frequency.

Overall, Figure 3 validates the semantic integrity of our classification scheme. It demonstrates that the link between a macro driver and firm performance is constructed through a specialized vocabulary that precisely maps distinct economic forces to specific corporate consequences.

4.3 Macro-Equity Logic Chains Appear in a Relatively Small Number of Equity Reports

Given the significant impact of macro events on the equity market, one might expect such information to be a focal point of analysts' equity evaluations. However, evidence from analyst reports suggests otherwise, highlighting potentially high cognitive costs of adopting them.

The pie chart in Panel B of Figure 2 illustrates this scarcity. Among all equity reports in our sample, only 19.2% contain vocabulary related to the macroeconomy. Furthermore, within this subset, only 42.7% incorporate at least one Macro-Equity Logic Chain (MELC). Therefore, Panel C shows that only 8.3% of all equity reports contain any MELCs. The subsequent nine rows present the fraction of reports containing specific types of MELCs. For instance, the seventh row (Logic Type 5) indicates that only 0.4% of equity reports contain explicit and causal reasoning focusing on the impact of the domestic economy on earnings and revenue. In Row 12 (Analyst MELC), we examine the distribution of MELC adoption across analysts; we find that approximately 79% of equity analysts have ever adopted a MELC during their careers. Finally, the last three rows detail the structure of reports containing logic chains. On average, these reports contain 2.8 MELCs. Of these, 2.0 logic chains have two elements ($A \rightarrow B$), and 0.8 have more than two elements ($A \rightarrow B \rightarrow \dots$).

In Figure 4, we plot the proportion of equity reports containing distinct types of MELCs over time. The solid black line represents MELCs of any type. Overall, the fraction is quite low; for instance, in the early years of the sample, MELCs appear in only about 5% of all equity reports. While the proportion of reports containing MELCs has increased since 2000, adoption spikes primarily during specific periods. One example is the 2008 Financial Crisis, where the fraction of reports with MELCs rose to nearly 13%.

However, the overall trend remains relatively flat and low.

When examining specific types of MELCs, the fraction is unsurprisingly lower and flatter. For instance, the share of reports containing MELCs driven by the domestic economy is generally below 2.5%, rising to roughly 5% during the 2008 Financial Crisis. A similar pattern holds for other chain types. A notable exception involves chains where Earnings & Revenue is the outcome; this fraction is very flat, remaining stable even during the 2008 crisis.

This figure offers several key takeaways. First, equity reports contain relatively few MELCs, suggesting that analysts do not commonly incorporate them into their evaluations.[4] Second, there is temporal variation in the ratio, which appears linked to macroeconomic conditions. For example, during the 2008 Great Financial Crisis—arguably the most significant financial event of recent decades—the ratio reached its peak. However, even at the height of the 2008 crisis, the vast majority of equity reports (87%) did not contain a single MELC. Moreover, as we show later, such time-series variation is significantly dwarfed by the cross-sectional variation arising from analyst-firm fixed effects.

Viewed through the lens of our conceptual framework, the low unconditional share of equity reports with MELCs suggests that, for most analysts, the expected gain from explicit macro reasoning remains below the cognitive costs that would occur.

5 Relationship Between Macro-Equity Logic Chains and Forecast Accuracy

5.1 Forecasts in Equity Reports with Macro-Equity Logic Chains are More Accurate

We next turn to the conceptual framework's performance implication: if MELCs help analysts map macro conditions into firm outcomes, forecasts in reports containing MELCs should be more accurate.

Importantly, one may be concerned that the low usage of MELCs is unrelated to the cognitive costs. Even in the absence of such chains in equity reports, analysts may still implicitly incorporate macro-related information when forming their equity forecasts. However, we find that this is unlikely to be the case. In

[4]This finding is consistent with the implications from Hugon et al. (2016), which document that equity analyst rarely use macroeconomic information.

particular, we find that analyst forecasts are more accurate for equity reports with MELCs, consistent with our conceptual framework. To do so, we link analyst forecasts from IBES to equity reports. We regress the absolute forecast errors on an indicator variable ($Logic$) that equals one if the equity report contains MELCs and zero otherwise. We employ a common measure of absolute forecast errors in the literature—absolute error scaled by the standard deviation of the absolute consensus forecast errors over the previous four years.

Table 5 presents the results. Specifically, we report results when we define $Logic$ by containing any MELC as well as by containing MELCs with specific macro topics (Commodity & Materials, Domestic Economy, and Monetary Policy) or equity topics (Equity Valuation, Earnings & Revenue, and Business Operations). The results for any MELC are reported in Column (1) and the results for specific macro or equity topics are in Columns (2) to (7).

Table 5 shows that the absolute forecast errors are statistically significantly smaller for equity reports containing any MELC. The point estimates of Columns (1) are negative and statistically significant at the 1% level. The economic magnitudes of the point estimates are sizable. Based on Column (1), having any MELCs in the equity report is associated with a decrease in the absolute forecast error by about 5% of its sample mean. This effect is not driven by any single type of MELCs. This is evident from the fact that the point estimates on the indicator variable $Logic$ are negative and significant at the 5% level across all the specifications.

These results are in line with the view that analysts' mental models of evaluating equities can be captured by the equity reports and that considering macro-equity reasoning helps analysts better forecast the earnings of equities. That is, the results support the prediction from the conceptual framework that relevant MELC adoption carries an accuracy premium.

Controlling for Macro Word Our construction of MELCs intends to capture direct causal macro-equity reasoning of analysts, which reflects analysts incorporating and linking specific macro information to their equity forecasts. One concern of our measure of MELCs is that it may only capture the attention of analysts to general macro information, which may also improve their forecast accuracy. We further show that MELCs contain information beyond merely capturing analysts' attention to general macro information.

We use the usage of simple macro words in equity reports to capture analysts' attention to macro information and show that MELCs provide additional information beyond simple macro words. Specifically, we construct a variable *Macro Word* that equals one if the equity report contains any macro word and repeat our analyses in Table 5, controlling for *Macro Word*. Because an equity report must contain macro words if it has MELCs, when *Macro Word* is controlled, the point estimate on $Logic$ measures the incremental power in reducing absolute forecast errors from MELCs. Therefore, if MELCs contain information above *Macro Word* in improving forecast accuracy, we would expect a negative and significant point estimate on $Logic$.

Table A3 in the Online Appendix reports the results. Consistent with the view that MELCs contain information beyond merely capturing analysts' attention to general macro information, the point estimates on $Logic$ are negative and significant across all specifications. Column 1 reports the results when we use all types of MELCs. The point estimate suggests that the improvement in forecast accuracy is about 50% larger than containing only macro words. Columns 2 to 7 show that all six types of MELCs contain information beyond *Macro Word*. The persistence of the accuracy premium after absorbing *Macro Word* frequency is consistent with the model implication that the accuracy gain derives from structured causal reasoning, not only from macroeconomic attention.

5.2 Components of Macro-Equity Logic Chains

5.2.1 Type of MELCs

We first examine whether the type of MELC an analyst employs matters. That is, MELCs not only capture analysts incorporating general macro information but also capture the linking of specific macro information to equity forecasts. We exploit cross-sectional variation in the relevance of macro information across stocks. If our results reflect analysts' ability to incorporate and connect specific macro signals to equity forecasts, then a given MELC type should matter more for stocks that are more exposed to the corresponding macro information.

As a proof-of-concept, we first show that MELCs in general matter more for stocks that are more affected by general macro information. To measure a stock's relevance to general aggregate information, we use the

stock's market beta. The benefit of market beta is that it is agnostic of the underlying macro information. Then, we repeat our baseline analyses on equity reports and forecast errors by interacting the experience measures and stocks' market betas, and examine whether the interaction terms are significant. Column 1 of Table 6 reports the finding for this subsample result. The variable of interest is the interaction terms. We find that the point estimates on the interaction terms are negative and significant at the 1% level, suggesting that the effect is indeed stronger among stocks with higher market betas.

Next, we turn to our analyses that study whether a given MELC type matters more for stocks that are more exposed to the corresponding macro information. As discussed above, we distinguish MELCs that relate to three types of macro information—Commodity & Materials, Domestic Economy, and Monetary Policy. Then, we examine whether each type aligns with the corresponding dimension of firm-level macro exposure. Specifically, we map Commodity & Materials logic chains to firms' commodity betas, Domestic Economy logic chains to GDP growth betas, and Monetary Policy logic chains to inflation betas. If a given type of MELC reflects analysts' deliberate reasoning about that specific macroeconomic channel and its relevance for equity forecasts, we expect the interaction between the specific logic chain variable and the corresponding firm beta to be negative and statistically significant.

These results are summarized in Columns 2, 4, and 6 of Table 6. Columns 2, 4, and 6 are on Commodity & Materials logic chains to firms' commodity betas, Domestic Economy logic chains to GDP growth betas, and Monetary Policy logic chains to inflation betas, respectively. We find that the interaction terms in these three specifications are negative and statistically significant at the 5% level. Moreover, in Columns 3, 5, and 7, we further include the interaction terms of each macro beta and the non-corresponding logic chains (i.e., firms' commodity betas interacted with non-Commodity & Materials logic chains). We find that the coefficient estimates for these interaction terms are statistically insignificant and tend to be smaller in magnitude. This result is consistent with the view that the MELC reflects analysts' deliberate reasoning about the particular macro channel and its relevance for equity forecasts.

Our conceptual framework predicts that the accuracy gain from MELC adoption is strictly increasing in the firm's sensitivity to the relevant macro factor. The significant interaction coefficient provides direct support for this prediction and is difficult to reconcile with models in which MELCs improve accuracy

through a generic attention channel.

5.2.2 Length of MELCs

We next study another component of MELCs: the length of MELCs. MELCs can be of different lengths—An important fraction of MELCs have only two elements, while others can have multiple elements. Two-element MELCs (A $\rightarrow$ B) are direct macro-equity statements, where a macro variable (i.e., inflation) causally affects an equity object directly (i.e., stock price). In contrast, longer MELCs (A $\rightarrow$ B $\rightarrow$ C $\rightarrow$ ...) have intermediate elements, and therefore represent a more complex reasoning process. Our conceptual framework predicts that MELCs with multiple elements should be less common and the improvement in forecast accuracy of adopting MELCs with multiple elements should be muted. This is due to the fact that longer chains introduce additional scope for misspecification and noise for each intermediate link.

Table A15 presents the results by separating MELCs into those with exactly two elements versus those with more than two elements, and relating each to forecast accuracy. The results show that both lengths are associated with improved forecast accuracy, but the magnitude of the coefficient estimate is substantially larger for two-element MELCs. In Column (1), Logic (2 Elements) is associated with a statistically significant reduction in absolute forecast error, while Logic (>¿ 2 Elements) is also negative and significant, but with only half the magnitude.

This pattern is even sharper when we condition on macro-cause categories. For example, for Commodity & Materials and Domestic Economy (Columns (2)–(3)), only the two-element indicator is reliably negative and significant, whereas the longer-chain indicator becomes economically small and statistically insignificant. A similar message emerges when conditioning on the equity outcome category. That is, short MELCs are associated with a larger improvement in forecast accuracy than longer MELCs.

Overall, our conceptual model predicts that the accuracy premium from adopting a logic chain declines as chain length increases, because compounding noise across layers worsens the deterministic signal. The decline in accuracy we observe for longer MELC is consistent with this prediction.

6 Drivers of Macro-Equity Logic Chains

In this section, we study the drivers of the adoption of MELCs, focusing on two implications from the conceptual framework: (i) persistent heterogeneity in the usage of MELC at the analyst-firm level, and (ii) experience as a force that lowers effective cognitive cost. We first decompose the variation in equity reports to examine the persistence of these logic chains, finding that adoption is driven largely by time-invariant analyst and firm factors rather than observable characteristics. Second, we show that analysts' past experience writing macro reports with MELCs serves as an important driver of this behavior—a result we confirm using cross-type heterogeneity tests and an instrumental variable approach.

6.1 Analyst-Firm Fixed Effects Explain a Large Fraction of the Variation

We start by decomposing the presence of MELCs in equity reports following the methodology of Giglio et al. (2021) and Kwan et al. (2025). Specifically, we define the indicator variable $Logic$, which equals one if the equity report contains MELCs and zero otherwise. Then, we regress $Logic$ on different sets of fixed effects, including time fixed effects, analyst fixed effects, firm fixed effects, and the combination of these fixed effects. Specifically, we run the following regression specifications:

$$Logic_{i,j,t} = a_{j,h,t} + \epsilon_{i,t}, \tag{1}$$

where i denotes equity report, t denotes time, j denotes analyst, and h denotes firm. $a_{j,h,t}$ can be time fixed effect only, analyst fixed effect only, firm fixed effect only, and combinations of these various fixed effects.

We report the results in Panel A of Table 7. The first row reports the results for overall MELCs. Time fixed effects explain little variation in the use of MELCs in equity reports, with a R^2 of less than 1%. On the other hand, the second and third columns highlight that the analyst fixed effects and firm fixed effects explain important fractions of the variation—the R^2 are 13.8% and 10.8%, respectively. When we include the Analyst $\times$ Firm fixed effects, the R^2 reaches 26.2%. Adding other fixed effects only marginally increases the explanatory power. When we include the full set of fixed effects of Analyst $\times$ Firm + Time $\times$ Analyst + Time $\times$ Firm, the R^2 only increases to 32.4%. Moreover, in Table A4 in the Online Appendix, we show that the usage of MELCs in equity reports is persistent even controlling for time and firm fixed effects. Its

persistence is even stronger than the persistence of the usage of MELCs in the macro reports.

The remaining nine rows of Panel A of Table 7 report the decomposition results for each specific MELC indicator. As discussed in Section 3, for the MELCs used in equity reports, the macro topics can be summarized into three broad groups (Commodity & Materials, Domestic Economy, and Monetary Policy) and the equity topics can also be grouped into three broad categories (Equity Valuation, Earnings & Revenue, and Business Operations), resulting in nine distinct types of MELCs.

The basic patterns are similar across the nine specific logic chains—time fixed effects explain less than 1% of the variation, while analyst and firm fixed effects can explain a more substantial portion of the variation. When we include the analyst-firm fixed effects, the R-Squareds increase to close to 25%. However, Panel A of Table 7 also reveals important heterogeneity across the nine MELCs. The magnitudes of the R^2s are similar across the three macro topics, but differ significantly for the equity topics. In particular, analyst-firm fixed effects can explain a large fraction of variation for MELCs involving Equity Valuation and Earnings & Revenue, but their explanatory power is much muted when the MELC involves Business Operations.

The importance of persistent cross-sectional dispersion in the usage of macro-equity logic in evaluating equities highlights the stickiness of reasoning and arguments analysts employ in their reasoning to evaluate equities. The large role of analyst-firm fixed effects is therefore consistent with stable pair-specific differences in relevance and cognitive cost as emphasized in our conceptual framework. The result also echoes recent experimental findings that highlight the stickiness of reasoning and arguments agents make (e.g., Andre et al. 2022; Andre et al. 2024; Andre et al. 2025).

6.1.1 The Role of Analyst and Firm Characteristics

Having established the importance of analyst-firm fixed effects in explaining variation in the use of MELCs, we next examine whether observable characteristics can explain why certain analyst-firm pairs are persistently more likely to employ them. To investigate this, we adopt a two-stage methodology similar to Giglio et al. (2021). In the first stage, we regress macro-equity logic indicators on analyst-firm fixed effects; in the second stage, we regress the estimated fixed effects on a set of observable attributes. Analyst characteristics include tenure, gender, and race, while firm characteristics include size, book-to-market ratio,

momentum, volatility, profitability, and age. We also control for the word count of the equity reports.

The results are reported in Panel B of Table 7, which displays the adjusted R^2 values for these regressions. The main takeaway is that observable analyst and firm characteristics explain very little of the variation in the estimated analyst-firm fixed effects. The adjusted R^2s range from 1% to 6%, depending on the specific MELC. These results remain robust when we restrict the sample to analyst-firm pairs with a higher number of reports, where the fixed effects are estimated more precisely.

In Table A7 of the Online Appendix, we regress $Logic_{i,j,t}$ on the same set of analyst and firm characteristics and report the coefficient estimates. Column (1) shows that, in the absence of fixed effects, the adjusted R^2 is only 8%, a finding consistent with our conclusion from Panel B of Table 7. Interestingly, analyst tenure does not significantly explain the use of MELCs, suggesting that the incorporation of macroeconomic information in equity forecasts does not naturally occur as the length of career accumulates over time. Moreover, basic analyst characteristics, such as gender and race, offer insignificant explanatory power regarding MELC usage.

6.2 Past Experience in Driving Macro-Equity Logic Chains

Given the stickiness of this adoption and the fact that observable characteristics have little explanatory power for MELC adoption, identifying its primary drivers remains a challenge. Our conceptual framework provides a potentially important driver that may influence the adoption of logic chains – analyst experiences. Moreover, prior work shows that past experiences are important determinants of belief formation and decision making (e.g., Malmendier and Nagel 2011, 2016), suggesting that analysts' earlier experiences may influence how they subsequently interpret and process information. Therefore, in this subsection, we examine whether these earlier experiences determine how analysts utilize MELCs.

A key advantage of our data is that we link each analyst to the complete history of their macroeconomic and equity research. Leveraging this feature, we document that analysts tend to employ similar types of MELCs across their macro and equity reports. Figure 5 illustrates that the nine major types of MELCs appear in both macro and equity reports, indicating substantial consistency in reasoning structure across report types. This feature naturally motivates our next test: whether analysts' prior experience writing macro

reports that rely on particular MELCs affects how they subsequently evaluate equities. In other words, we ask whether exposure to MELCs in macro reports carries over to analysts' future equity analysis.

6.2.1 Measuring Experiences

To capture analysts' exposure to the MELC from writing macro reports, we construct two measures. First, we construct an indicator, $Exp^{Indicator}$, which is a dummy variable that equals one if the focal analyst demonstrated exposure to the MELC in macroeconomic reports within the past two years, and zero otherwise. Second, we construct an alternative experience measure, $Exp^{Weighted}$, that computes a weighted average of an analyst's complete historical experience, following the approach of Malmendier and Nagel (2011). Specifically, for each analyst j at date t, we calculate the weighted average of past exposures to the MELC as:

$$\begin{aligned} Exp_{j,t}^{Weighted} &= \sum_{k=1}^{tenure_{j,t}-1} w_{j,t}(k,\lambda) \cdot I_{t-k}, \\ \text{where } w_{j,t}(k,\lambda) &= \frac{(tenure_{j,t}-k)^{\lambda}}{\sum_{k=1}^{tenure_{j,t}-1}(tenure_{j,t}-k)^{\lambda}}. \end{aligned} \tag{2}$$

Here, I_{t-k} is an indicator variable that equals 1 if the analyst issued a macroeconomic report containing the MELC in quarter $t-k$. The weights w_{jt} depend on three factors: the analyst's tenure at time t ($tenure_{jt}$), the recency of the past experience (k), and a decay parameter λ that governs how rapidly the influence of past experiences diminishes.

The parameter λ determines the weighting pattern: when $\lambda < 0$, more distant experiences receive greater weight than recent ones; when $\lambda = 0$, weights are constant and $Exp^{Weighted}$ becomes a simple average of all past experiences; and when $\lambda > 0$, weights decrease from recent to distant experiences (with concave decay for $\lambda < 1$, linear for $\lambda = 1$, and convex for $\lambda > 1$). We directly adopt the λ in Malmendier and Nagel (2011) and convert their baseline annual parameter ($\lambda = 1.5$) to a quarterly equivalent ($\lambda = 1.125$).

6.2.2 Effects on the Usage of Adoption in Equity Reports

We examine how the experiences of writing macro reports with MELCs affect the evaluation of equities by analysts. Specifically, we investigate whether the experience of writing macro reports with MELCs is

associated with a higher likelihood of having these logic chains in their subsequent analyst reports. We employ the following regression specifications:

$$Logic_{i,j,t} = \beta \times Exp_{j,t} + \beta^{'} \times X_{i,t} + FE + \epsilon_{i,j,t} \tag{3}$$

where i is the index for report, j for analyst, t for time. Exp can be either $Exp^{Indicator}$ or $Exp^{Weighted}$. In all specifications, we control for the length of the report using *Word Count*, calculated as the natural logarithm of the report's total word count.

Table 8 documents the results. Columns (1) to (3) use $Exp^{Indicator}$ to measure these experiences, defined as an indicator variable that equals one if an analyst issued a macroeconomic report with MELC in the past two years, and Columns (4) to (6) use $Exp^{Weighted}$ as our measurement, which is a continuous version of past experience with heavier discounting of more distant past as defined in Section 3.

In Column (1), we only include time fixed effects. The point estimate on $Exp^{Indicator}$ is positive and significant at the 1% level. When we include broker fixed effects, the point estimate decreases marginally from 10.9% to 9.2%, and remains highly significant. Column (3) reports our preferred specification, including time, broker, and analyst fixed effects. The point estimate on $Exp^{Indicator}$ remains positive and statistically significant at the 1% level at 0.8%. The economic magnitude is sizable—having recent experience of writing macro reports with MELC is associated with 0.8% higher probability of including this logic chain in subsequent equity reports. We reach a similar conclusion when we use $Exp^{Weighted}$ as the independent variable. In our preferred specification in Column (6), the point estimate is positive and highly statistically significant—a one-standard deviation increase in $Exp^{Weighted}$ is associated with a 0.8% increase in the probability of including MELC in subsequent equity reports. Furthermore, in Section 8, we provide a specification based on an instrumental variable where we continue to find similar effects. These results show that past experience of writing macro reports with MELCs is positively and significantly associated with the probability of analysts using similar logic in their future equity reports. These findings are consistent with the idea that these experiences affect the way analysts evaluate equities.

We then plot the dynamics of the point estimates around these experiences of writing macro reports with MELCs. The results are shown in Figure 7. There are several takeaways from this figure. First, there

are no significant differences between the treatment and control groups prior to these experiences of writing macro reports with MELCs. In other words, there is no pre-trend between the treatment and control groups, supporting the parallel trend assumption needed to identify the effect of having these experiences on analysts' equity evaluations. Second, we find that there is a reversal of the effect that takes about two quarters, and tends to stabilize afterwards, suggesting that the effect is strongest when the experience is the most salient in mind.

Furthermore, our results in the previous section show that the usage of MELC is associated with lower forecast errors. If our results are driven by past experiences inducing analysts to apply similar logic in their equity evaluation, these experiences, thus, may lead to lower analysts' equity forecast errors. Consistent with this idea, Table A12 in the Online Appendix shows that analyst forecast errors significantly decrease subsequent to the experience of writing macro reports with MELCs.

Taken together, our results are consistent with the conceptual framework that experience-based reductions in cognitive cost are a key driver of MELC adoption.

6.2.3 Domain-Specificity in Macro-Equity Logic Chain Adoption

In the baseline analysis, we show that the past experiences of writing macro reports containing MELCs lead to a significant increase in the likelihood of usage of MELCs in analysts' subsequent equity reports. However, as we discussed in Section 3, there is rich heterogeneity in the MELCs employed by analysts in their macro reports and equity reports.

Therefore, we design a rigorous test using this rich heterogeneity. The basic idea is that, if analysts' reasoning is indeed driven by their past experience, we should expect to find that past experiences of a specific MELC would lead to an increase in usage of the same MELC in equity evaluation. To test this hypothesis, we conduct a set of tests in the following form:

$$Logic_{i,j,m,t} = \beta_{m,k} \times Exp_{j,k,t} + \beta^{'} \times X_{j,t} + FE + \epsilon_{i,j,t} \tag{4}$$

where i indexes the report, j the analyst, and t the time. The indices m and k denote, respectively, the m-th type used in the current equity report and the k-th type of logic chain used in past macroeconomic reports.

Because there are nine different MELCs as discussed in Section 3, there are, in total, 81 regressions run.

We summarize the information of these 81 regressions in Figure 6. Each square in the figure shows the coefficient $\beta_{m,k}$ normalized by the total effect of all MELC types from the macro reports, or $\sum_{l=1}^{9} \beta_{m,l}$. The normalization is done so that the coefficient estimates across different MELC types from the macro reports can be compared in one figure.

Darker color in the figure means that the normalized coefficients are larger. If past experiences of a specific type of MELC more likely to increase the usage of the same type of MELC in equity evaluation, we would find that the colors of the diagonal are darker in color. Indeed, we find that the colors of the diagonal squares tend to be the darkest for each topic, consistent with the view that the results are driven by their past experiences on MELCs of similar types. This finding is broadly consistent with the domain-specificity of experience effects (Malmendier and Nagel (2011); Malmendier (2021)).

6.2.4 Instrumental Variable Approach

A potential concern of the baseline specification is that writing MELCs in macro reports is an endogenous choice: an omitted variable may jointly affect an analyst's choice in using MELCs in macro reports and equity reports simultaneously. Although we show that there is no pre-trend in Figure 7, which renders this possibility unlikely, we further address endogeneity in this subsection by adopting an instrumental variables (IV) approach to examine how past experience with MELCs in macro reports affects analysts' reasoning in equity evaluations.

Specifically, we instrument our variable of interest—$Exp^{Indicator}$ or $Exp^{Weighted}$—with the past experience of using MELCs in macro reports of the macro report team's lead analyst of the focal analyst. The relevance condition requires that the lead analyst's past use of MELCs in macro reports predicts a non-lead analyst's exposure to MELCs in macro reports, as captured by $Exp^{Indicator}$ or $Exp^{Weighted}$. This condition is likely to hold because macro reports are produced in teams where the lead analyst plays a central role in structuring the analysis and determining the reasoning framework. Analysts exhibit persistent analytical styles, and lead analysts with a history of using MELCs tend to continue organizing macro reports around such logic chains. As a result, non-lead analysts who participate in these teams are likely more

exposed to MELCs, regardless of their own prior tendencies. We also confirm the relevance condition with first-stage IV regression.

The exclusion restriction requires that the lead analyst's past reliance on MELCs affects a non-lead analyst's equity forecast reasoning only through the non-lead analyst's exposure to MELCs. This assumption is plausible because the instrument is based on the lead analyst's historical behavior in macro reports, and thus does not directly capture the non-lead analyst's equity-specific forecasting style. Moreover, lead analysts do not directly author or oversee non-lead analysts' equity reports. In other words, any influence on equity reasoning arises only through shared exposure during macro-report collaboration. Conditional on analyst fixed effects and other controls, assignment to macro teams led by MELC-heavy analysts is unlikely to be driven by unobserved shocks to non-lead analysts' equity evaluation behavior, supporting the validity of the exclusion restriction.

The results are documented in Table 9. First, we find that the first-stage point estimates are uniformly positive and highly statistically significant, indicating that the instrument is strongly relevant. That is, lead analysts who more frequently employ MELCs in their prior macro reports are more likely to include MELCs in current macro reports. The table also shows that the second-stage regressions based on different specifications are consistently positive and statistically significant, supporting our baseline results that past exposures of MELCs in macro reports drive analysts' usage of similar logic chains in their subsequent equity evaluation.

7 Market Impact

The previous two sections examine the properties and drivers of MELCs in equity research. In this section, we turn to their economic consequences. Specifically, we investigate whether the equity market responds differentially to analysts who frequently employ MELCs. We do this by comparing market reactions to recommendation revisions issued by analysts who regularly incorporate MELCs in their equity analysis against those who rarely do so. To evaluate these reactions, we utilize two standard methodologies: a panel regression approach and portfolio analysis.

7.1 Panel Regression Approach

We begin by quantifying the immediate market reaction to recommendation revisions using a panel regression framework. Our primary dependent variable is the signed cumulative abnormal return, namely $SignedCAR[0, +T]$, defined as:

$$SignedCAR[0, +T] = Sign(Revision) \times CAR[0, +T] \tag{5}$$

Here, the variable $CAR[0, +T]$ represents the cumulative abnormal return over a window of T days (where $T = 1,\ 2,$ or 3), and we use the cumulative market returns in this window as the adjustment. A shorter window (small T) captures the immediate price response to analyst recommendations, while a longer window accounts for potential post-announcement drifts. $Sign(Revision)$ captures the direction of the recommendation change—if the market acknowledges the opinion of the focal analyst, the direction of market reaction should be consistent with the sign of the revision. This specification allows us to capture both the magnitude and direction of the market reaction following the recommendation revision.

The key explanatory variable, $MELCs$, is the analyst's historical propensity to utilize MELCs in their equity analysis. We measure this by aggregating an analyst's MELC usage in the equity reports across all prior quarters of their tenure, applying a quarterly decay factor of 1.125 to emphasize recent behaviors. We regress the signed CAR, $Sign(Revision) \times CAR[0, +T]$, on this historical usage metric $MELC$. A positive and statistically significant coefficient would indicate that the market reacts more strongly to recommendation revisions by analysts who give MELCs more weight in their equity reports.

Table 10 presents the regression results. To isolate the effect of MELCs, our specifications control for standard cross-sectional return predictors—including Size, Book-to-Market (BM), Momentum (Mom), Volatility, Profitability and firm age ($LnAge$). Columns 1 through 3 report the results for event windows of [0, +1], [0, +2], and [0, +3], respectively.

The results provide strong support for our hypothesis. The coefficients on historical MELC usage are positive and statistically significant at the 1% level across all specifications. This suggests that the market does not view all recommendation revisions equally; rather, it reacts more strongly to revisions issued by analysts who adeptly integrate macro-equity logic chains in their equity analysis. In terms of economic

magnitude, the effect is substantial: a one-standard-deviation increase in an analyst's past MELC usage is associated with a 10.8 basis point increase in the immediate directional market reaction.

7.2 Portfolio Sorting

To complement the panel regression analysis, we employ portfolio sorting techniques to further examine the relationship between MELC usage and market reactions. This non-parametric approach relaxes the linearity assumptions inherent in the regression framework.

At the end of each month t, we sort all stock recommendations into quintile portfolios based on the issuing analyst's historical MELC propensity, as defined by the $MELCs$ variable introduced in the previous subsection. Portfolio Q1 (Low) consists of recommendations from analysts with the lowest historical MELC usage, while Q5 (High) comprises those from analysts with the highest usage. For all stock recommendations issued in month $t+1$ within a given quintile, we compute the average signed cumulative abnormal return, $SignedCAR[0,+T]$, following Equation 5. To isolate the specific impact of the revision and control for firm-specific heterogeneity, we adjust this metric by subtracting the firm's average signed cumulative abnormal return, calculated over a rolling two-year window.

Table 11 presents the results of this non-parametric analysis. The data reveals a clear monotonic relationship: using a two-day window, the long-short strategy (Q5 minus Q1) yields an abnormal return of 25 basis points, statistically significant at the 5% level. The signed CARs increase progressively from Q1 to Q5, indicating that market reactions intensify as the analyst's reputation for macro-equity logic strengthens. These results remain robust when extending the window to three or four days and align with the findings from the panel regression.

Overall, our analysis demonstrates that the equity market responds more strongly to recommendations issued by analysts who frequently employ MELCs. In other words, the market impact of recommendations from these analysts is significantly larger. These findings support the interpretation that the equity market recognizes a strong association between MELC usage and more accurate forecasts.

8 Additional Results and Robustness Checks

8.1 Logic Chains and Valuation Methods

A potential concern is that our MELC may simply proxy for analysts' broader mental models in equity valuation, in particular, their valuation method. A recent paper by Bastianello et al. (2024) shows that valuation approaches, such as multiples-based or discounted cash flow (DCF), employed by analysts significantly affect their forecast accuracy. To differentiate our effect from this channel, we repeat our baseline forecast error regression, conditional on the valuation method employed in the report. Specifically, we randomly select 10% of all matched earnings reports and, following Bastianello et al. (2024), we use LLMs to classify the valuation method used in these equity reports. We then estimate the baseline specification within each subsample of valuation method, including P/E, any multiples-based methods, and DCF methods.

Table 12 presents the results. Across all valuation-method subsamples, the coefficient on $Logic$ stays negative and statistically significant. Moreover, the magnitudes of the point estimates are quantitatively similar to those of the full sample estimate. For example, the point estimate is -32.6 among P/E reports, -39.4 among reports using any multiples, and -37.0 among DCF and other non-multiple reports. These results show that our main results are not driven by analysts choosing different valuation methods.

8.2 Robustness Checks on the Driver of Macro-Equity Logic Chains

8.2.1 Lead Analyst vs. Non-Lead Analysts

In our baseline results, we construct analysts' past experience regardless of whether they are the lead analysts in the macro reports. One concern is that writing MELCs in macro reports is an endogenous choice, and a missing variable may affect an analyst's choice in using MELCs in macro reports and equity reports simultaneously. Although we show that there is no pre-trend in Figure 7, which renders this possibility unlikely, in this subsection, we focus on analysts' past experience as non-lead analysts to mitigate this concern further.

The lead analysts are typically the main contributors to the qualitative aspects of analyst reports Gao et al. (2021). Therefore, it is less likely that the non-lead analysts endogenously choose to include macro-equity

logic in the macro reports. Table A8 shows the results, where we construct the equivalences of $Exp^{Indicator}$ and $Exp^{Weighted}$ using the lead analyst sample and the non-lead analyst sample, respectively.

We find that the point estimates for both the lead analyst and the non-lead analyst are positive and significant at the 5% level across all six specifications. Moreover, the point estimates using the past experiences measured using the non-lead analyst sample tend to be larger. For example, when $Exp^{Indicator}\ (Lead)$ and $Exp^{Indicator}\ (NonLead)$ are both included in the regression, the point estimate of $Exp^{Indicator}\ (NonLead)$ is more than twice as large as that of $Exp^{Indicator}\ (Lead)$. Similar results are observed when we use the $Exp^{Weighted}\ (NonLead)$ and the $Exp^{Weighted}\ (Lead)$ measures. These results suggest that our baseline point estimates may actually be a lower bound, and the actual effect may even be larger. This downward bias may be due to the fact that using macro-equity logic is a persistent characteristic of analysts across writing macro and equity reports.

8.2.2 Analysts with Few Experiences in Writing Macro Reports

Our second additional analysis is to repeat our baseline analyses of the adoption of MELCs in equity reports in the subsample of analysts with few experiences in writing macro reports. The idea is that these analysts are less likely to endogenously choose to write macro reports, and are more likely to be required to write a macro report. Although we show that there is no pre-trend in Figure 7, this test can further mitigate the concern that analysts with macro-equity mindsets endogenously choose to participate more in writing macro reports with MELCs.

Table A9 presents the results. Column (1) examines a subsample of analysts with a below median frequency of writing macro reports. Column (2) focuses on a subsample of analysts with a below median number of macro reports. Column (3) builds on Column (2) by further restricting the sample to analysts whose average time gap between consecutive macro reports is above the population median. Column (4) also builds on Column (2) by further restricting the sample to analysts who do not serve as the lead analysts in any of the macro reports they wrote. We find that the coefficient estimates for the variable of interest, $Exp^{Weighted}$, are positive and statistically significant across all four specifications.

8.2.3 Past Experiences During High Economic Uncertainty

Our baseline results are based on all past experiences of writing macro reports with MELCs. In this subsection, we construct an alternative version of past experiences by only focusing on macro reports with MELCs during periods of high economic uncertainty. The idea is that, during high economic uncertainty, brokers are more likely to experience a capacity constraint in producing macro reports. Therefore, an equity analyst is more likely to be required to write a macro report in these episodes, rather than endogenously choosing to write one. Accordingly, we construct alternative versions of $Exp^{Indicator}$ and $Exp^{Weighted}$ only using past experiences of writing macro reports with MELCs during high economic uncertainty periods, where we measure economic uncertainty using the economic policy uncertainty measure from Baker et al. (2016).

The results are reported in Table A10. In Columns (1) and (2) of Table A10, we use the alternative versions of $Exp^{Indicator}$ and $Exp^{Weighted}$, respectively. The point estimates for these two experience measures are positive and statistically significant at the 1% level. Furthermore, in Columns (3) and (4), to better capture the unexpectedness of such arrangements, we impose an additional requirement that the analyst is a non-lead contributor to the macro report. The results remain both qualitatively and quantitatively similar. Overall, these findings demonstrate that our results are robust to this refinement.

8.3 Stacked DiD

Recently, there have been growing concerns about the validity of the standard staggered difference-in-differences (DiD) design, where treatment timing varies across units. When treatment effects are heterogeneous across cohorts or over time, the conventional two-way fixed-effects (TWFE) estimator may produce biased and misleading estimates, as already-treated units are incorrectly used as controls for later-treated ones (e.g., Cengiz et al. 2019; Callaway and Sant'Anna 2021; Sun and Abraham 2021). Therefore, as an additional analysis, we adopt the stacked DiD approach, which constructs separate cohort-specific datasets that include only units first treated in a given period and those not yet treated during the corresponding event window. These datasets are then "stacked" and estimated jointly, ensuring that comparisons are made only

between appropriate treated and untreated units, thereby eliminating contamination from already-treated observations and yielding unbiased cohort-specific average treatment effects.

The results are shown in Table A11 in the Online Appendix. Columns (1) and (2) of Table A11 estimate the effect within a $[-2, +2]$ month window, while Columns (3) and (4) use a $[-3, +3]$ month window of the analyst's first experience of macro-equity logic in macro reports. Across all the specifications, we find that the point estimates on the cross-term of Treat $\times$ Post are positive and statistically significant at the 1% level. These results confirm our baseline finding that analysts' prior exposure to MELCs in macro reports significantly affects their subsequent usage of macro-equity arguments in equity reports.

8.4 Robustness Checks on Market Impact

In this subsection, we provide additional robustness tests regarding how MELC experience affects market reactions to analysts' stock recommendations. We construct our dependent variable $SignedCAR$ by subtracting the two-day cumulative abnormal return from the return on a DGTW portfolio matched on size, book-to-market (B/M), and momentum characteristics Daniel et al. (1997). Results are reported in Table A13. The positive relationship between prior MELC exposure and the signed CARs around the stock recommendation remains robust. In Table A14, we further sort the signed cumulative abnormal return based on analyst's historical MELC propensity in their macro reports. The coefficient estimates on the experience measure remain positive and statistically significant. These results suggest that the market impact of MELC experience is robust across alternative specifications and experience sources.

9 Conclusion

This paper studies how equity analysts explicitly link macroeconomic information to firm-level outcomes in their valuation and forecasting process. Leveraging a comprehensive career-level dataset of analyst macroeconomic and equity reports, and using large language models to extract explicit causal reasoning, we introduce and document macro-equity logic chains (MELCs)—direct causal reasoning that maps macroeconomic information to equity outcomes. We show that such reasoning is surprisingly uncommon in equity

research, appearing in fewer than ten percent of equity reports.

We then show that the presence of MELCs is economically meaningful. Equity forecasts issued in reports containing MELCs are significantly more accurate, and this improvement is not driven by general attention to macroeconomic conditions or by stylistic differences in report writing. Instead, the accuracy gains are strongest when the specific type of macro-equity logic aligns with the corresponding firm-level exposure to the corresponding macroeconomic channel. These results indicate that MELCs capture analysts' ability to integrate and correctly map relevant macroeconomic information into firm-level forecasts, rather than merely reflecting broader macro attention.

We then examine the persistence and origins of macro-equity reasoning. We show that the use of MELCs is highly persistent at the analyst-firm level and is largely unexplained by observable analyst or firm characteristics, pointing to stable differences in analysts' reasoning frameworks. Exploiting variation in analysts' past experience writing macroeconomic reports, we provide evidence that exposure to MELCs in macro research affects subsequent equity evaluations. Analysts who gain experience with specific types of macro-equity logic are more likely to apply the same logic in later equity reports and to improve their forecast accuracy, with effects that are strongest following recent exposure. Together, these findings highlight the role of experience in shaping analysts' mental models and demonstrate how structured economic reasoning develops and persists. Beyond forecast accuracy, MELCs also have significant implications for equity market outcomes. We show that the equity market responds more strongly to recommendation revisions issued by analysts who more frequently employ macro-equity logic in their equity research.

Viewed through the lens of our conceptual framework, our evidence points to a coherent pattern: analysts use MELCs selectively, benefit from using them when they are relevant, and adopt them more readily as experience lowers cognitive cost.

Our findings have broader implications for research on belief formation, and information processing, and mental models in financial markets. By directly observing analysts' causal reasoning rather than inferring beliefs from prices or outcomes, we provide field evidence on how structured economic reasoning affects financial market outcomes. The results suggest that differences in analysts' macro-equity reasoning—partially shaped by past experiences of analysts—help explain heterogeneity in forecast performance and market

impact. More broadly, our approach demonstrates how advances in LLM can be used to study economic reasoning at scale, opening new avenues for research on expectations, narratives, and decision-making in the capital market. More broadly, the results suggest that cognitive costs, relevance, and accumulated experience jointly shape how structured macro reasoning enters financial forecasts.

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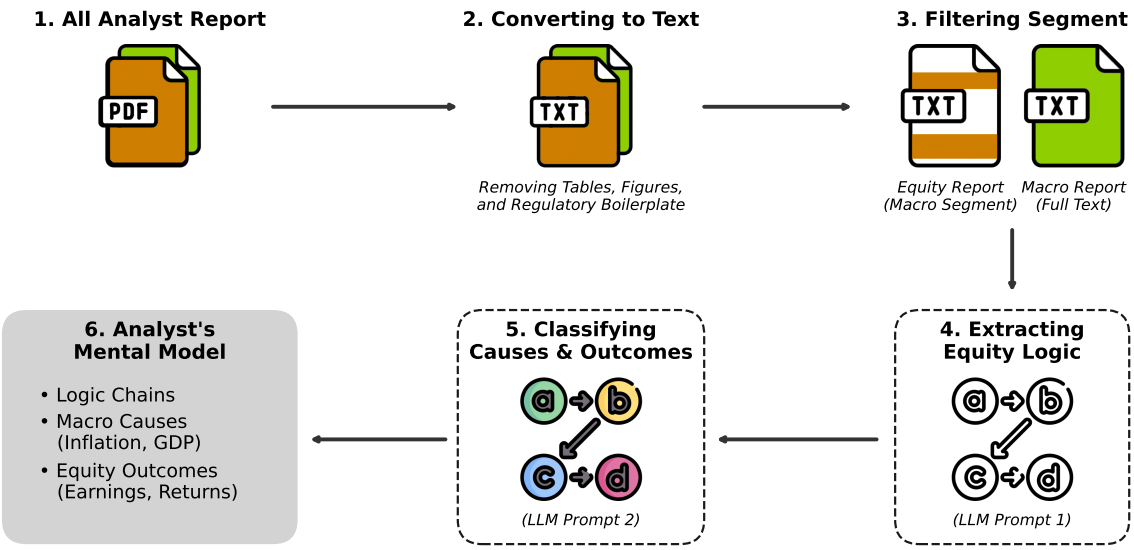


Figure 1: Workflow of the Macro-Equity Logic Chain Extraction Method

This figure presents the workflow of our macro-equity logic chain extraction methodology. The underlying dataset comprises 5 million equity reports and 250,000 macroeconomic reports, covering the period from 1998 to 2024.

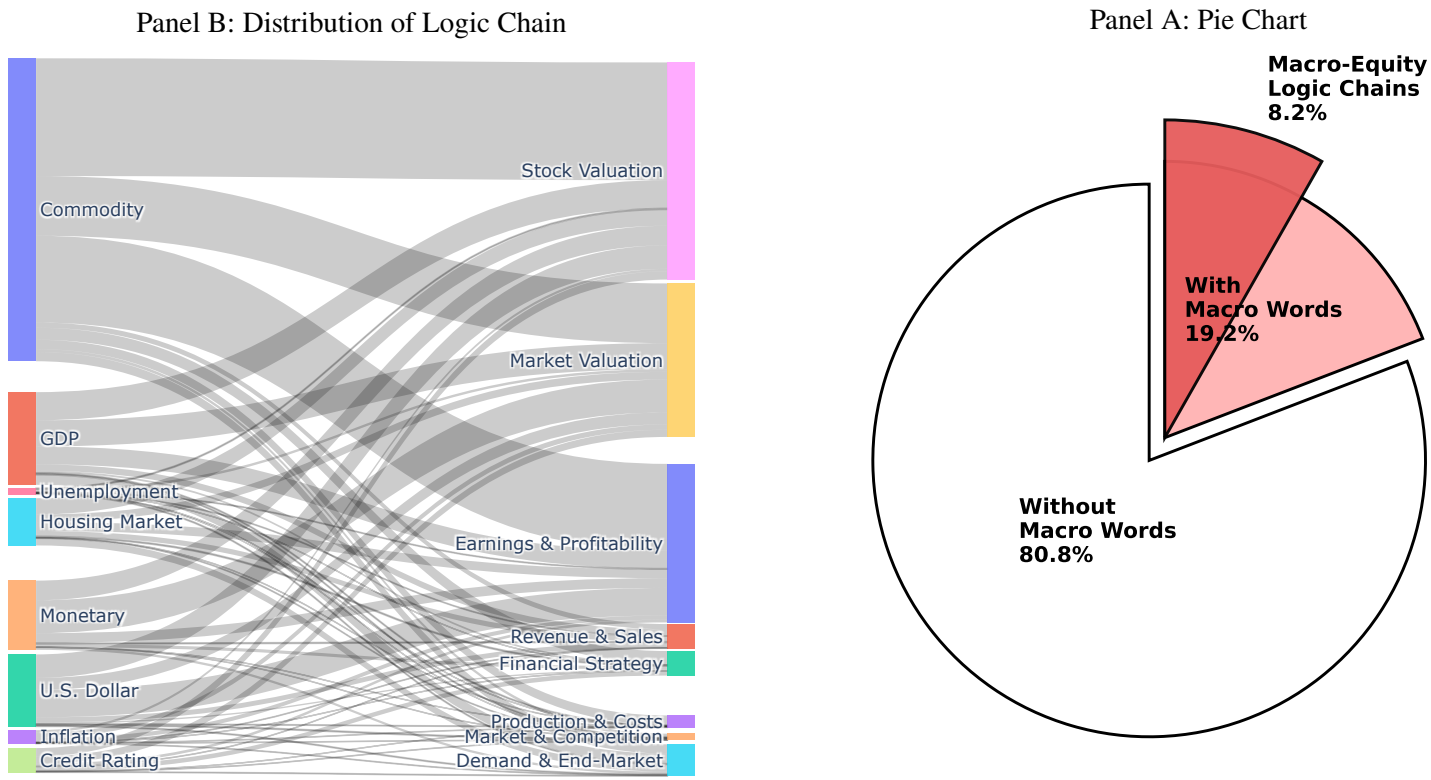


Figure 2: Macro-equity Logic Chains in Equity Reports

This figure illustrates the prevalence and structural landscape of macro-equity logic chains within equity reports. On the left, a Sankey diagram visualizes the structural distribution of macro-equity logic chains across the sample. The source bars on the left – ordered from top to bottom as Commodity & Materials, Domestic Economy, and Monetary Policy – represent the "Causes". These flow into the "Outcome" bars on the right: Equity Valuation, Earnings & Revenue, and Business Operations. The height of each bar corresponds to the number of relevant logic chains. The width of the flows is proportional to the frequency of each specific group of logic chains. On the right, a pie chart illustrates the proportion of reports containing general macroeconomic terminology versus those with explicit macro-equity logic chains.

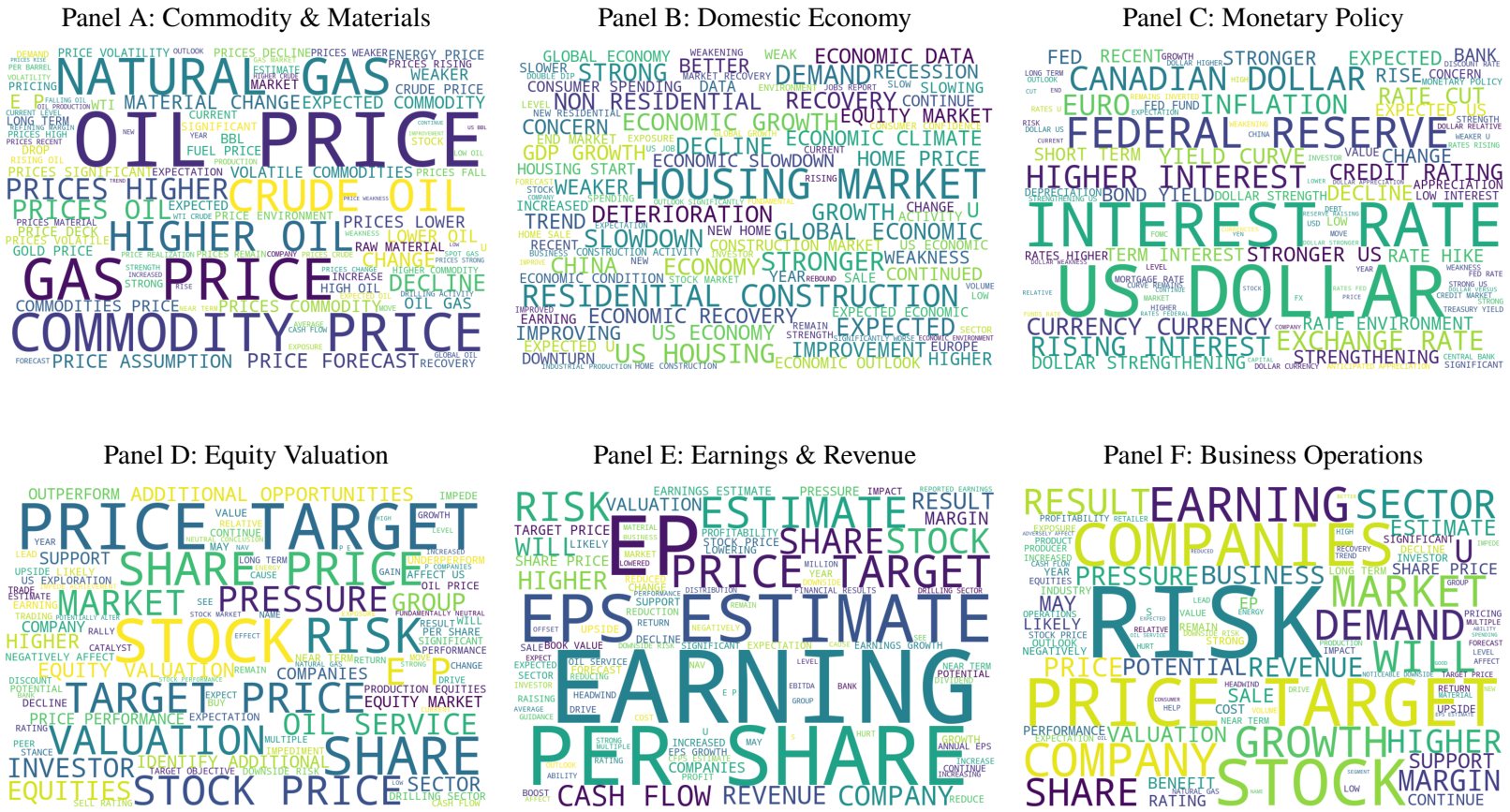


Figure 3: Word Cloud of Macro-Equity Logic Chains

This figure illustrates the vocabulary of macro-equity logic chains found in equity reports. The top row visualizes terms associated with macroeconomic causes, grouped into three categories: (1) Commodity & Materials, (2) Domestic Economy, and (3) Monetary Policy. The bottom row depicts terms related to equity outcomes, classified into: (1) Equity Valuation, (2) Earnings & Revenue, and (3) Business Operations. In each word cloud, word size is proportional to its relative frequency within that specific category.

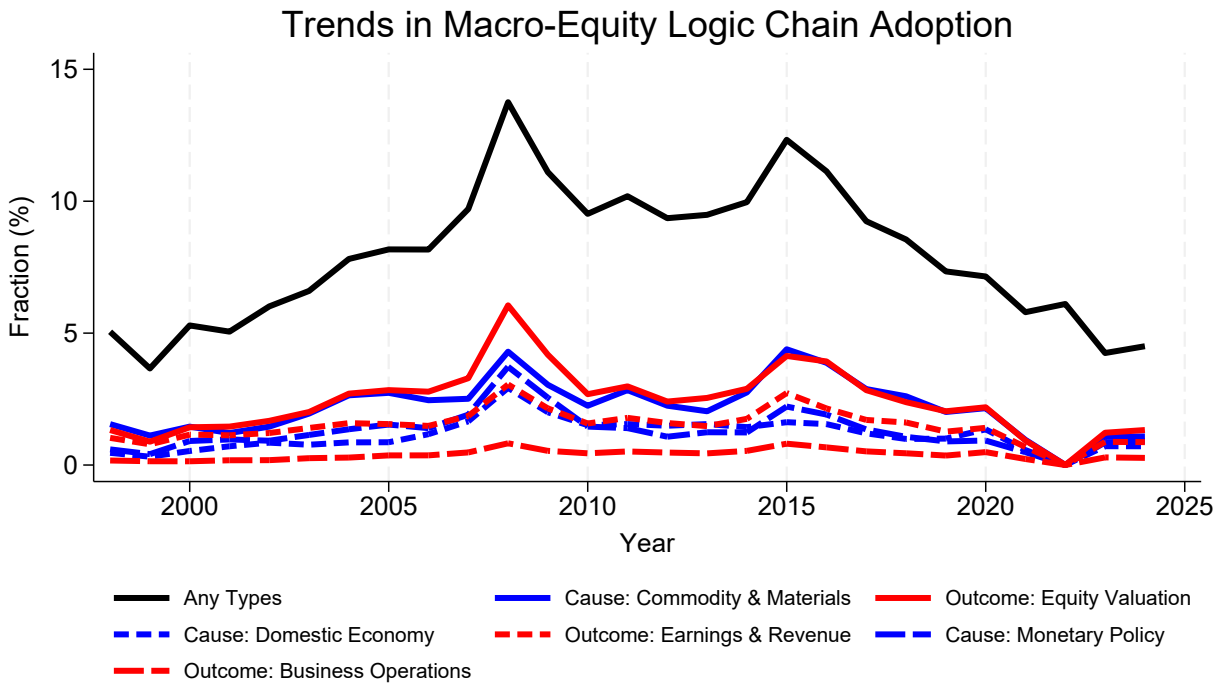


Figure 4: Ratio of Equity Report with Macro-Equity Logic Chains

This figure plots the proportion of equity reports containing macro-equity logic chains over the period 1998–2024, with values on the y-axis expressed as percentages. The solid black line represents the fraction of equity reports containing any types of macro-equity logic chains. The blue lines represent the fraction of reports containing specific macroeconomic causes, categorized into: (1) Commodity & Materials, (2) Domestic Economy, and (3) Monetary Policy. The red lines represent the fraction of reports containing specific equity outcomes, categorized into: (1) Equity Valuation, (2) Earnings & Revenue, and (3) Business Operations.

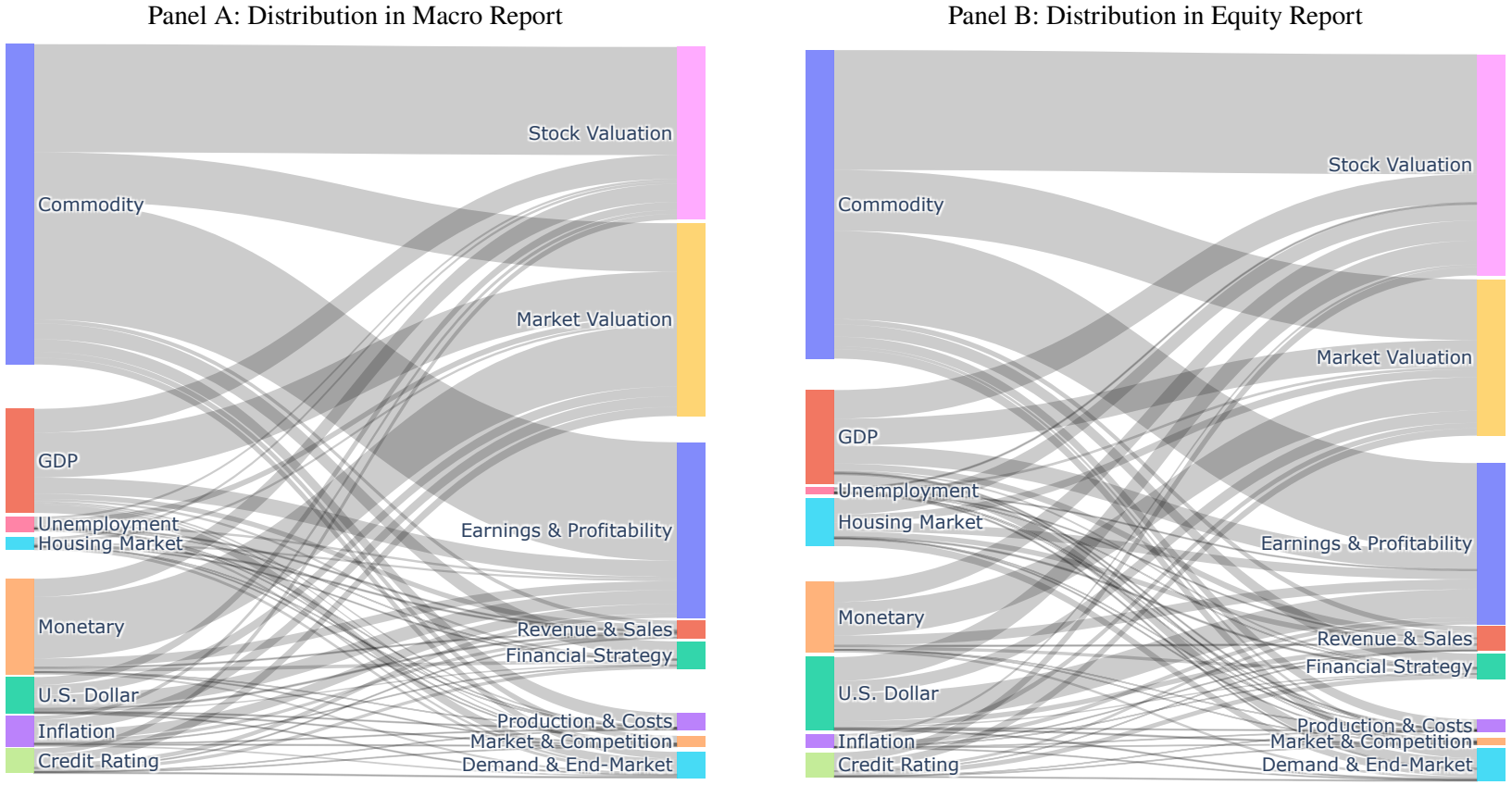


Figure 5: Macro-Equity Logic Chains: Macroeconomic Reports vs Equity Reports

This figure visualizes the distribution of macro-equity logic chains. On the left, a Sankey diagram visualizes the structural distribution of macro-equity logic chains in the macroeconomic reports. The source bars on the left – ordered from top to bottom as Commodity & Materials, Domestic Economy, and Monetary Policy – represent the "Causes". These flow into the "Outcome" bars on the right: Equity Valuation, Earnings & Revenue, and Business Operations. The height of each bar corresponds to the number of relevant logic chains. The width of the flows is proportional to the frequency of each specific group of logic chains. On the right, the Sankey diagram replicates the one in Figure 2, demonstrating the distribution of macro-equity logic chains in equity reports.

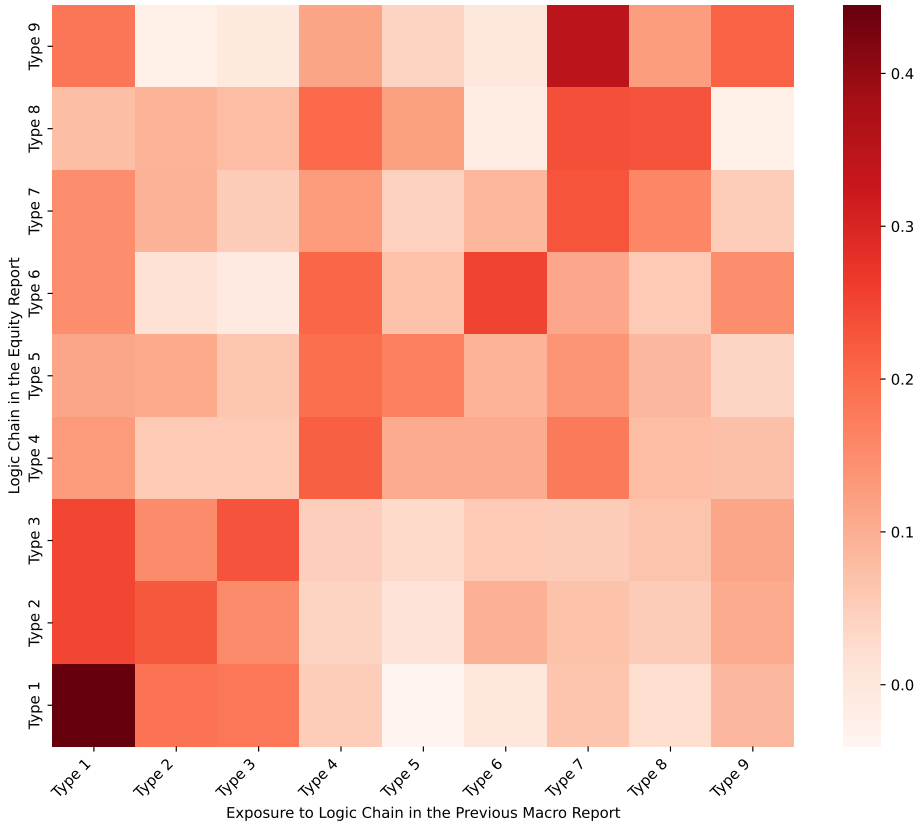


Figure 6: The Effect of Type-Specific Past Experience on Macro-Equity Logic Chain Adoption

This figure illustrates how an analyst's prior experience with specific macro-equity logic chains influences their subsequent use of those chains in equity reports. It is constructed based on the following regression model:

$$Logic_{i,s,m,t} = \beta_{m,k} \times Exp_{i,k,t}^{Indicator} + \beta' \times X_{s,t} + FE + \epsilon_{i,s,t}$$

where i indexes the analyst, s the stock, and t the time. The indices m and k denote the logic chain type used in the current equity report and the logic chain type used in past macroeconomic reports, respectively.
To generate the plot for a given pair (m, k), we normalize the coefficient $\beta_{m,k}$ by the total effect of all logic chain types from the macroeconomic reports, $\sum_{l=1}^{9} \beta_{m,l}$. This normalization shows the relative importance of experience with type k for adopting type m.

The analysis covers nine distinct macro-equity logic chains (Types 1-9). These chains link three macroeconomic causes, ordered as "Commodity & Materials," "Domestic Economy," and "Monetary Policy," to three equity-related outcomes, ordered as "Equity Valuation," "Earnings & Revenue," and "Business Operations." For example, Type 1 captures the logic "Commodity & Materials $\rightarrow$ Equity Valuation," while Type 9 represents "Monetary Policy $\rightarrow$ Business Operations." For a detailed description of these logic chains, please refer to Panel C of Table 3.

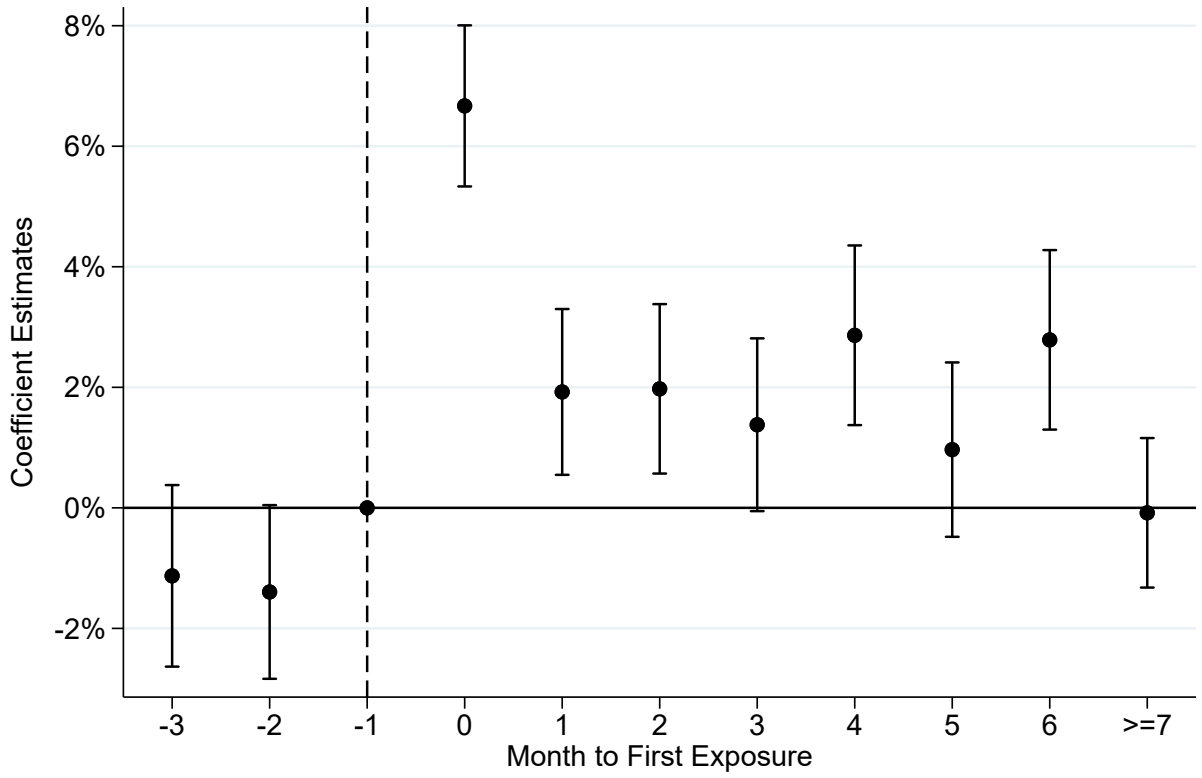


Figure 7: Parallel Trend

This figure examines analysts' adoption of macro-equity logic in equity reports surrounding their first exposure to such logic chains when writing macroeconomic reports. Each coefficient represents an estimate from the following regression specification:

$$Logic_{j,t} = \sum_{k=-3}^{-2} \beta_k \times D_{j,t+k} + \sum_{k=0}^{7} \beta_k \times D_{j,t+k} + \beta' \times X_{j,t} + \text{FE} + \epsilon_{j,t},$$

where j denotes the analyst and t denotes time. The estimation is performed at the analyst-month level. The graph plots the coefficient estimates and confidence intervals from month $t-3$ to $t+7$ relative to the month of first exposure. The regression includes analyst and month fixed effects, with standard errors clustered at the analyst level. The sample period spans from 1998 to 2024.

Table 1: LLM Prompt

This table provides the two prompts utilized in this paper. Panel A presents the extraction prompt for identifying macro-equity logic chains in equity reports. Panel B then presents the classification prompt for categorizing these logic chains by their macroeconomic causes and equity-related outcomes.

Panel A: Extracting Macro-Equity Logic Chains from Equity Reports

```
TASK: Analyze a provided equity analyst report to identify, extract, and
categorize explicit causal logic chains, with a specific focus on those impacting
equities.

PART 1 - EXTRACT ALL LOGIC CHAINS
A "logic chain" is a causal sequence where one element (variable/condition/event)
leads to another.  Each logic chain has the form:  "A → B → C → ...", with each
element explicitly connected to the next through causal phrases, such as:
1.  because / since / as / due to / owing to / result from
2.  drives / leads to / causes / results in / impacts / affects
3.  therefore / thus / consequently / hence
4.  pressures / supports / hurts / boosts / increases / decreases, etc.

Format per chain:  [# (unique identifier), "A → B → C → ...", "Quote"]

Critical Constraints:
1.  EXPLICITLY CAUSAL RELATIONSHIP ONLY. Omit if i) descriptive, ii) correlative
("associated with"), iii) predictive ("might"), or iv) sequential events without
clear causation.
2.  MULTI-STEP CHAINS FROM SINGLE SENTENCE rather than breaking into separate
chains when a single sentence (paragraph) contains multiple consecutive causal
links.
3.  PRESERVE EXACT WORDING in QUOTE. Concisely summarize chain element that
preserve the original meaning and directional cues.
4.  EACH CHAIN SELF-CONTAINED and derived from a single, explicit causal sentence
(paragraph).

PART 2 - IDEDNTIFY EQUITY-RELATED CHAINS
Filter Part 1 chains with elements containing equity terms such as:
1.  tickers / companies / sectors
2.  equity (market) / stock (market / indices) / share prices / returns
3.  valuations / earnings / price targets / market cap / P/E

For each equity-related chain, extract element number of the equity-related term.
If "A → stock return increases" then equity element number is 2.  If equity terms
appear in multiple elements, specify the last element number.

Format:  [# (from Part 1), equity_element_number]
```

(*Continued*)

```
Critical Constraints:
1.  Include only when equities are the subject or object of explicit causation.
2.  Exclude chains where equity terms appear only in company names (e.g., "Apple
reported") without explicit causal effect on equity prices/markets.
3.  Focus on chains where macro or financial variables have a direct causal
effect on equities.

VALIDATION: All elements in the a logic chain are distinct, each causally
connected to the next.

OUTPUT to txt:
{
     "All":  [[1, "A → B → C", "Quote"], ...]  or "No Logic",
     "Equity":  [[1, 2], ...]  or "No Logic"
}
```

Panel B: Classifying Macro Causes and Equity Outcomes

```
TASK: Classify Causes and Effects in Logic Chains Extracted from Analyst Report

PART 1:  CAUSE CLASSIFICATION
Classify INITIAL driver(s) into MACROECONOMIC categories:

1.  Commodity:  Prices of raw materials / physical goods
2.  GDP: Overall economic growth / activity levels
3.  U.S. Dollar:  Currency exchange rates / dollar strength
4.  Inflation:  General price levels / purchasing power
5.  Monetary:  Central bank policies / interest rates
6.  Housing Market:  Residential real estate / mortgage markets
7.  Unemployment:  Labor market conditions / employment levels
8.  Credit Rating:  Credit quality / borrowing conditions
9.  Other:  Non-macroeconomic or unclassifiable
*Choose the most macroeconomic and relevant cause*

PART 2:  EFFECT CLASSIFICATION
Classify FINAL outcome into EQUITY categories:

A. EQUITY VALUATION
A1.  Stock Valuation:  Specific stock price changes, outperformance /
underperformance, or "buying opportunity"
A2.  Market Valuation:  Broader market sentiment, risk appetite, volatility, or
general equity performance

B. EARNINGS & REVENUE
B1.  Earnings & Profitability:  Impacts on earnings (EPS, EBITDA), cash flow
(CFPS, FCF), or profit margins
```

(*Continued*)

```
B2. Revenue & Sales: Impacts on top-line revenue, sales volumes, or payment
volumes
B3. Financial Position & Strategy: Impacts on balance sheets, credit ratings,
M&A activity, or capital allocation

C. BUSINESS OPERATIONS
C1. Production & Costs: Changes in production levels, operational efficiency,
capacity, or cost structures
C2. Market & Competitive Position: Shifts in market share, competitive
landscape, pricing power, or regulatory outcomes
C3. Demand & End-Market Health: Changes in end-market demand, customer
behavior, or industry trends

D. OTHER: Non-equity or unclassifiable
*Choose most direct effect*

Output to txt (e.g. [10000, 4]: [5, A2]):
{
    [id#, order#]: [Cause#, Effect#],
    ...
}
```

Table 2: Logic Chain Examples

This table provides examples of macro-equity logic chains extracted by generative AI. For each example, we present the textual segment that explicitly articulates how a macroeconomic event or environment affects an equity outcome. Each element in the extracted cause-and-effect logic chain is shown with its corresponding category displayed in boldface.

Extracted Logic Chain:
Lower US unemployment rate (Unemployment) → Maintain peakish valuation (Stock Valuation)

Original Quote: Peakish Valuation Likely To Hold At Least A Few More Quarters. We believe prospects for EPS upside, comp acceleration, the company's 100% exposure to the US market, and potential for the US unemployment rate to go lower could help the shares maintain a peakish valuation.

This equity report was written by Rupesh Parikh from Oppenheimer & Co. for The Kroger Co. (KR) released on 2015/02/02.

Extracted Logic Chain:
Declining home prices (Housing Market) → Raised loan loss provision outlook (Financial Strategy)

Original Quote: Mortgage credit costs are looking to be substantial over the next 12-18 months. In early December, WM again raised its loan loss provision outlook, citing continued deterioration in the mortgage markets and declining home prices. WM expects a 4Q provision of $1.5b to $1.6b, or twice the level WM expects for net charge-offs, which were $445m in the 3Q.

This equity report was written by Robert P. Napoli from Piper Jaffray & Co. for Washington Mutual (WM) released on 2008/01/16.

Extracted Logic Chain:
Lack of access to financing (Credit Rating) → ASTE's revenues adversely affected (Revenue & Sales)

Original Quote: Anticipated end-market growth may not materialize. ASTE is currently expecting to see significant growth in its Infrastructure business on the back of the Federal Highway Bill, among other favorable expectations. Were incremental demand fail to materialize, the company's revenues and earnings could be adversely affected. These headwinds could come from improved utilization of existing road-building equipment, lack of access to financing, or competitors' pricing and sales actions.

This equity report was written by Michael D. Shlisky from Seaport Global Securities for Astec Industries (ASTE) released on 2018/07/25.

Extracted Logic Chain:
Cooling of inflation (Inflation) → Better margin expansion (Earnings & Profitability)

Original Quote: A cooling of inflation could generate upside. We think there is good visibility on improved pricing for GPK in the year ahead but anticipate most of the benefit will be offset by continued cost inflation. If inflation cools sooner and/or more dramatically than we are anticipating, GPK could see better margin expansion than we have been assuming.

This equity report was written by Mark A. Weintraub from Seaport Global Securities for WestRock Company (WRK) released on 2020/02/24.

Table 3: Cause and Effect Category Definitions

This table details the hierarchical classification process for the causes and outcomes of macro-equity logic chains. We employ LLMs to categorize extracted causes and outcomes into specific subgroups before aggregating them into broader classes. Panel A outlines the classification for causes, which maps eight specific categories into three broader groups: Commodity & Materials, Domestic Economy, and Monetary Policy. Panel B describes the categorization for the effects on equity outcomes, where nine LLM-generated subgroups are consolidated into three broad classes: Equity Valuation, Earnings & Revenue, and Business Operations. Panel C defines the nine distinct logic chain types resulting from the intersection of these broad classifications. See Table 1 for more details on the LLM procedure.

Classification	Category	Description
	Panel A: Cause	
Commodities & Materials	Commodity	Prices of raw materials or physical goods
Domestic Economy	GDP	Overall economic growth or activity levels
	Unemployment	Labor market conditions or employment levels
	Housing Market	Residential real estate or mortgage markets
Monetary Policy	Monetary	Central bank policies or interest rates
	U.S. Dollar	Currency exchange rates or dollar strength
	Inflation	General price levels or purchasing power
	Credit Rating	Credit quality or borrowing conditions
	Panel B: Effect	
Equity Valuation	Stock Valuation	Specific stock price changes or performance
	Market Valuation	Broader market sentiment, risk appetite, or volatility
Earnings & Revenue	Earnings & Profitability	Earnings (EPS), cash flow (CFPS), or profit margins
	Revenue & Sales	Top-line revenue, sales volumes, or payment volumes
	Financial Strategy	Balance sheets, credit ratings, or M&A activity
Business & Operations	Production & Costs	Production levels, operational efficiency, or cost structures
	Market & Competition	Market share, competitive landscape, or pricing power
	Demand & End-Market	End-market demand, customer behavior, or industry trends
	Panel C: Logic Chain	
	Type 1	Commodity & Materials → Equity Valuation
	Type 2	Commodity & Materials → Earnings & Revenue
	Type 3	Commodity & Materials → Business Operations
	Type 4	Domestic Economy → Equity Valuation
	Type 5	Domestic Economy → Earnings & Revenue
	Type 6	Domestic Economy → Business Operations
	Type 7	Monetary Policy → Equity Valuation
	Type 8	Monetary Policy → Earnings & Revenue
	Type 9	Monetary Policy → Business Operations

Table 4: Summary Statistics

This table presents summary statistics, with Panel A for the analyst equity report sample, Panel B for the matched earnings forecast sample, and Panel C for the landscape of MELC usage. The demographic variables *Male* and *White* are indicator variables that equal one if the analyst is male or white, respectively. *Report Gap* measures the average number of days elapsed between two consecutive reports issued by the same analyst. *Team Size* captures the total number of analysts who contributed to a given sample report. *Log Analyst Tenure* represents the logarithm of the number of years since an analyst first appeared in the sample. *Word Count* is the natural logarithm of the total words in a report. $Exp^{Indicator}$ is a dummy variable that equals one if an analyst participated in writing macroeconomic reports containing macro-equity logic chains over the past two years. $Exp^{Weighted}$ captures the weighted average of such exposure across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. *Abs Error / Std Past Error* represents the absolute forecast errors scaled by standard deviation of past forecast error over the previous four years. *Size* is the log of market capitalization. *BM* denotes the book-to-market ratio. *Mom* refers to the cumulative excess return from month $t-12$ to $t-2$. *Profitability* is measured as EBITDA scaled by total assets. *LnAge* is the natural logarithm of firm age in months. *Macro Word* and *Logic* are indicator variables equal to one if the report contains words related to the macroeconomy, or contains an MELC, respectively. *Logic Type 1 to 9* are indicator variables equal to one if the report contains a specific type of MELC, corresponding to the types defined in Table 3. *Analyst MELC* equals one if an analyst has used an MELC at least once during their tenure. *Number of MELC* equals the total number of MELCs used in an equity report.

	N	Mean	StDev	Min	P25	P50	P75	Max
Panel A: Analyst Equity Report								
Male	9,756	0.753	0.429	0.000	0.767	1.000	1.000	1.000
White	9,756	0.704	0.456	0.000	0.000	1.000	1.000	1.000
Report Gap	9,475	25.419	57.489	0.752	2.564	5.641	19.394	389.000
Team Size	4,437,420	1.755	1.147	1.000	1.000	1.000	2.000	7.000
Word Count	4,437,420	7.026	0.816	4.868	6.486	6.995	7.522	9.295
Log Analyst Tenure	6,223,231	1.840	0.814	0.076	1.235	1.903	2.495	3.289
$Exp^{Indicator}$	6,223,231	0.392	0.488	0.000	0.000	0.000	1.000	1.000
Exp^{Weight}	6,223,231	0.154	0.265	0.000	0.000	0.013	0.172	1.000
Panel B: Matched Earnings Forecast								
Abs Error / Std Past Error	1,073,006	7.314	13.167	0.000	0.857	2.731	7.590	86.461
Size	1,073,006	8.253	1.876	3.978	6.929	8.222	9.581	12.512
BM	1,073,006	0.566	0.559	0.021	0.223	0.411	0.719	3.619
Mom	1,073,006	13.384	47.507	-76.338	-14.603	8.099	32.168	217.958
Volatility	1,073,006	10.734	6.898	2.259	6.004	8.896	13.338	39.646
Profitability	1,073,006	10.018	14.318	-58.204	4.973	11.334	17.241	39.733
LnAge	1,073,006	5.269	0.922	3.178	4.625	5.352	5.971	6.987

Panel C: Landscape of Macro-Equity Logic Chain

	N	Mean	StDev	Min	P25	P50	P75	Max
Macro Word	4,437,420	0.192	0.394	0.000	0.000	0.000	0.000	1.000
Logic	4,437,420	0.082	0.275	0.000	0.000	0.000	0.000	1.000
Logic Type 1	4,437,420	0.014	0.118	0.000	0.000	0.000	0.000	1.000
Logic Type 2	4,437,420	0.008	0.092	0.000	0.000	0.000	0.000	1.000
Logic Type 3	4,437,420	0.002	0.045	0.000	0.000	0.000	0.000	1.000
Logic Type 4	4,437,420	0.006	0.080	0.000	0.000	0.000	0.000	1.000
Logic Type 5	4,437,420	0.004	0.062	0.000	0.000	0.000	0.000	1.000
Logic Type 6	4,437,420	0.002	0.045	0.000	0.000	0.000	0.000	1.000
Logic Type 7	4,437,420	0.007	0.084	0.000	0.000	0.000	0.000	1.000
Logic Type 8	4,437,420	0.005	0.071	0.000	0.000	0.000	0.000	1.000
Logic Type 9	4,437,420	0.001	0.027	0.000	0.000	0.000	0.000	1.000
Analyst MELC	9,756	0.791	0.406	0.000	1.000	1.000	1.000	1.000
Number of MELC	365,119	2.757	2.276	1.000	1.000	2.000	3.000	13.000
Number of MELC (2 elements)	365,119	1.979	2.083	0.000	1.000	1.000	3.000	11.000
Number of MELC ($>$ 2 elements)	365,119	0.748	1.123	0.000	0.000	0.000	1.000	6.000

Table 5: Forecast Error From Report With and Without Macro-Equity Logic Chain

This table presents regression results analyzing the effect of macro-equity logic chains on analyst forecast errors. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the previous four years. The key explanatory variable, *Logic*, is an indicator equal to one if the forecast is associated with an equity report containing a macro-equity logic chain of the specific type shown in the column headers, and zero otherwise. Column (1) reports results for logic chains of any type. Columns (2) through (4) examine chains driven by three specific causes: Commodities & Raw Materials, Domestic Economy, and Monetary Policy. Columns (5) through (7) focus on chains resulting in three specific effects: Equity Valuation, Earnings & Revenue, and Business Operations. All specifications control for firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

Dependent Variable: Absolute Error / Std Past Error							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any Type	Cause			Effect		
Sample Category		Commodity & Materials	Domestic Economy	Monetary Policy	Equity Valuation	Earnings & Revenue	Business Operations
Logic	-36.678***	-33.421***	-46.800***	-57.130***	-41.412***	-38.664***	-48.678***
	(-7.12)	(-4.06)	(-4.95)	(-6.93)	(-6.82)	(-6.17)	(-5.14)
Size	118.423***	115.398***	112.313***	112.318***	117.495***	113.359***	112.749***
	(17.88)	(17.39)	(16.21)	(16.40)	(17.67)	(17.01)	(16.49)
BM	40.633***	40.950***	46.705***	45.243***	42.523***	41.014***	46.602***
	(4.14)	(4.15)	(4.54)	(4.45)	(4.32)	(4.13)	(4.63)
Mom	-0.440***	-0.426***	-0.502***	-0.496***	-0.429***	-0.470***	-0.479***
	(-7.37)	(-7.10)	(-8.44)	(-8.35)	(-7.21)	(-7.95)	(-8.02)
Volatility	2.580***	2.838***	2.887***	2.982***	2.748***	2.834***	2.972***
	(5.88)	(6.26)	(6.23)	(6.51)	(6.19)	(6.28)	(6.45)
Profitability	3.815***	3.678***	4.082***	3.982***	3.756***	3.918***	3.933***
	(10.14)	(9.75)	(10.26)	(10.22)	(9.97)	(10.27)	(10.10)
LnAge	-412.939***	-422.001***	-423.901***	-422.029***	-418.570***	-415.293***	-423.824***
	(-27.45)	(-26.61)	(-26.21)	(-26.04)	(-27.33)	(-26.74)	(-26.15)
Adjusted R-Squared	0.178	0.181	0.183	0.182	0.180	0.180	0.183
N	1,056,240	904,566	880,318	880,893	986,122	947,221	866,588
Analyst FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Fiscal Year FE	YES	YES	YES	YES	YES	YES	YES

Table 6: Forecast Error By Distinct Macro Betas

This table investigates whether employing different types of macro-equity logic chains reduces analyst forecast errors for firms with high exposure to specific macroeconomic factors. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the prior four years. The variable *Key Logic* is an indicator equal to one if a forecast is associated with an equity report containing the specific type of macro-equity logic chain indicated by the column header. The variable *Other Logic* is an indicator equal to one if a forecast is associated with an equity report containing a logic chain with a cause type distinct from the key logic. These logic indicators are interacted with *High Key Beta*, a top-quintile dummy indicating firm-level exposure to specific macroeconomic factors: CAPM beta in Column (1); Commodity beta in Columns (2) and (3); GDP Growth beta in Columns (4) and (5); and Inflation beta in Columns (6) and (7). The CAPM beta is estimated by regressing the firm's monthly returns on market excess returns over the prior two years, while the Commodity beta is estimated analogously using returns on the Bloomberg Commodity Index. The GDP Growth beta is estimated using expected GDP growth (following Vassalou (2003)), and the Inflation beta is estimated using inflation innovations derived from an AR(1) model. All specifications control for the key beta dummy, key logic dummy, firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Absolute Error / Std Past Error						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Key Beta	CAPM Beta	Commodity Beta		GDP Growth Beta		Inflation Beta	
Key Logic	Any Logic	Commodity & Materials		Domestic Economy		Monetary Policy	
High Key Beta x Key Logic	-21.476***	-33.501**	-34.821***	-36.820**	-38.095**	-51.565***	-48.122***
	(-4.67)	(-2.56)	(-2.61)	(-1.99)	(-2.01)	(-2.93)	(-2.69)
High Key Beta x Other Logic			-5.211		1.392		-7.250
			(-0.30)		(0.11)		(-0.58)
Control	YES	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.178	0.178	0.178	0.178	0.178	0.179	0.179
N	1,056,240	1,056,240	1,056,240	1,056,240	1,056,240	1,056,240	1,056,240
Analyst FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Fiscal Year FE	YES	YES	YES	YES	YES	YES	YES

Table 7: Analysts' Adoption of Macro-Equity Logic Chains: Fixed Effects Decomposition

This table presents the results of a fixed effects decomposition for the adoption of various macro-equity logic chains. In Panel A, we report the adjusted R^2 values from regressions of specific macro-equity logic chain indicators (rows) on different sets of fixed effects (columns). We examine time, analyst, and firm fixed effects individually, as well as their pairwise interactions. In Panel B, we link analyst-firm interactive fixed effects to analyst and firm-level characteristics. We employ a two-stage procedure: first, we regress macro-equity logic indicators on analyst-firm fixed effects; second, we regress the estimated fixed effects on observable characteristics, including analyst tenure, gender, race, firm size, book-to-market ratio, momentum, volatility, profitability, firm age, and report word count. We report the adjusted R^2 from the second regression. All values are expressed as percentages.

Panel A: Fixed Effects Decomposition

Sample Category	R^2 (Percent) of Panel Regression									
	(1) Time (T)	(2) Analyst (A)	(3) Firm (F)	(4) T × A	(5) A × F	(6) F × T	(7) T × A + A × F	(8) A × F + F × T	(9) F × T + T × A	(10) T × A + A × F + F × T
Any Types of Macro → Equity	0.7	13.8	10.8	18.8	26.2	17.1	29.9	29.8	25.5	32.4
Commodity & Materials → Equity Valuation	0.2	13.4	10.4	19.1	24.0	16.0	28.1	27.6	24.8	30.3
Commodity & Materials → Earnings & Revenue	0.1	6.6	5.2	9.8	13.8	9.5	16.2	16.6	14.6	18.4
Commodity & Materials → Business Operations	0.0	2.0	1.6	3.4	7.4	4.1	8.4	9.2	6.3	10.1
Domestic Economy → Equity Valuation	0.2	4.0	3.1	7.1	13.8	7.4	16.1	16.4	12.4	18.3
Domestic Economy → Earnings & Revenue	0.1	2.2	2.5	4.4	11.0	6.3	13.1	13.7	9.6	15.4
Domestic Economy → Business Operations	0.0	1.1	1.4	2.3	7.2	4.2	8.0	8.9	5.7	9.5
Monetary Policy → Equity Valuation	0.5	12.2	5.8	16.6	23.2	13.2	26.5	26.2	22.5	28.9
Monetary Policy → Earnings & Revenue	0.1	2.7	2.1	5.9	13.6	6.3	16.3	16.2	11.2	18.3
Monetary Policy → Business Operations	0.0	0.9	0.8	2.2	6.5	3.4	7.3	7.7	5.1	8.3

Panel B: Analyst-Firm Fixed Effect and Characteristics

	R^2 (Percent) of Panel Regression			
	(1) Report ≥ 1	(2) Report ≥ 3	(3) Report ≥ 5	(4) Report ≥ 10
Any Types of Macro → Equity	5.9	5.3	4.6	4.0
Commodity & Materials → Equity Valuation	1.3	1.3	1.3	1.3
Commodity & Materials → Earnings & Revenue	1.2	1.2	1.2	1.3
Commodity & Materials → Business Operations	0.2	0.3	0.3	0.4
Domestic Economy → Equity Valuation	1.1	1.1	1.1	0.8
Domestic Economy → Earnings & Revenue	0.6	0.7	0.6	0.6
Domestic Economy → Business Operations	0.3	0.3	0.3	0.3
Monetary Policy → Equity Valuation	4.5	4.7	4.2	2.7
Monetary Policy → Earnings & Revenue	0.8	0.8	0.7	0.7
Monetary Policy → Business Operations	0.1	0.1	0.1	0.1

Table 8: Analysts' Adoption of Macro-Equity Logic Chains: Effect of Analysts' Past Experiences

This table examines whether analysts' prior exposure to macro-equity logic chains – gained through past experiences in macroeconomic reporting – influences their subsequent adoption of such logic in equity reports. The dependent variable, *Logic*, is an indicator equal to one if an equity report contains a macro-equity logic chain, and zero otherwise. The key explanatory variables capture analysts' past exposure: $Exp^{Indicator}$ is a dummy variable equal to one if the analyst participated in writing macroeconomic reports containing macro-equity logic chains within the past two years; $Exp^{Weighted}$ is the weighted average of such exposure over the analyst's entire tenure, calculated using a quarterly decay factor of 1.125, following Malmendier and Nagel (2011). *Word Count* is the natural logarithm of the total number of words in the report. T-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic					
	(1)	(2)	(3)	(4)	(5)	(6)
$Exp^{Indicator}$	10.915***	9.181***	0.784***			
	(22.22)	(20.01)	(5.64)			
$Exp^{Weighted}$				26.394***	24.182***	2.689***
				(22.64)	(20.57)	(3.82)
Word Count	7.201***	6.774***	6.824***	7.072***	6.803***	6.823***
	(37.29)	(43.68)	(45.62)	(37.19)	(44.11)	(45.59)
Adjusted R-Squared	0.093	0.122	0.251	0.116	0.142	0.251
N	6,223,231	6,223,227	6,222,950	6,223,231	6,223,227	6,222,950
Year FE	YES	YES	YES	YES	YES	YES
Broker FE	NO	YES	YES	NO	YES	YES
Analyst FE	NO	NO	YES	NO	NO	YES

Table 9: Instrumental Variable

This table employs an instrumental variable (IV) approach to examine how an analyst's prior exposure to macro-equity logic chains affects their subsequent adoption of such logic in equity reports. The dependent variable, *Logic*, is an indicator equal to one if an equity report contains a macro-equity logic chain, and zero otherwise. The key explanatory variables measure analysts' past exposure: $Exp^{Indicator}$ is a dummy variable equal to one if the analyst participated in writing macroeconomic reports containing macro-equity logic chains within the past two years; $Exp^{Weighted}$ represents the weighted average of such exposure over the analyst's entire tenure, calculated using a quarterly decay factor of 1.125. Columns (1)–(4) instrument past exposure using an indicator on whether the analyst's former macro supervisors possessed macro-equity logic experience. Columns (5)–(8) use an instrument based on the average macro-equity logic experience of the analyst's former macro supervisors. *Word Count* is the natural logarithm of the total number of words in the report. T-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic							
Instrument	Dummy: Supervisor's Macro-Equity Exp.				Avg: Supervisor's Macro-Equity Exp.			
	(1) 1st-stage	(2) 2nd-stage	(3) 1st-stage	(4) 2nd-stage	(5) 1st-stage	(6) 2nd-stage	(7) 1st-stage	(8) 2nd-stage
IV	59.008***		13.305***		22.776***		22.834***	
	(45.49)		(26.34)		(7.83)		(10.56)	
$\widehat{Exp}^{Indicator}$		1.787***				15.356***		
		(5.24)				(3.38)		
$\widehat{Exp}^{Weighted}$				7.926***				15.317***
				(5.16)				(3.61)
Word Count	-0.118	6.824***	-0.026	6.824***	0.036	11.275***	0.115	11.262***
	(-1.34)	(45.66)	(-0.57)	(45.55)	(0.43)	(39.78)	(1.53)	(39.55)
Adjusted R-Squared	0.673	0.046	0.860	0.046	0.593	0.067	0.878	0.072
N	6,222,950	6,222,950	6,222,950	6,222,950	1,487,382	1,487,382	1,487,382	1,487,382
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: Market Impact

This table examines the influence of macro-equity logic chains on the market impact of analyst stock recommendations. The dependent variable is the signed cumulative abnormal return, measured over a two-, three-, or four-day window beginning on the recommendation date. The signed CAR for a recommendation on stock i is defined as:

$$SignedCAR_i[0,+T] = \text{Sign}(Revision_i) \times \left[\prod_{t=0}^{T} (1 + R_{i,t}) - \prod_{t=0}^{T} (1 + R_{Mkt,t}) \right],$$

where $T+1$ represents the window length, $R_{i,t}$ denotes the raw stock return on day t, and $R_{Mkt,t}$ represents the market return on day t. The key explanatory variable, $MELCs$, captures the frequency with which an analyst adopted macro-equity logic chains in equity reports prior to the focal recommendation. This variable is calculated over the analyst's prior tenure using a quarterly decay factor of 1.125. Control variables include firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. The t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans 1998 to 2024. All coefficients are multiplied by 100.

	SignedCAR$[0,+1]$	SignedCAR$[0,+2]$	SignedCAR$[0,+3]$
	(1)	(2)	(3)
$MELCs$	60.416***	47.250***	44.459***
	(4.05)	(2.92)	(2.61)
Size	-24.236***	-29.149***	-33.940***
	(-4.05)	(-4.49)	(-4.83)
BM	13.666*	14.872*	6.824
	(1.93)	(1.91)	(0.71)
Mom	-0.374***	-0.344***	-0.372***
	(-5.59)	(-4.73)	(-4.84)
Volatility	1.926***	1.719***	1.541**
	(3.41)	(2.85)	(2.44)
Profitability	-1.633***	-1.423**	-1.281**
	(-3.29)	(-2.57)	(-1.99)
LnAge	-70.127***	-68.722***	-73.371***
	(-7.29)	(-6.60)	(-6.52)
Adjusted R-Squared	0.212	0.199	0.187
N	212,881	212,881	212,881
Analyst FE	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 11: Market Impact - Portfolio Sorting

This table employs a portfolio sorting approach to evaluate the influence of macro-equity logic chains on the market reaction to analyst stock recommendations. At the end of each month t, recommendations are sorted into quintile portfolios based on the analyst's $MELCs$ value, as defined in Table 10. We report the portfolio average signed cumulative buy-and-hold abnormal return (signed CAR) for all recommendations issued in month $t + 1$. The signed CAR is adjusted by subtracting the firm-specific average signed CAR computed over a rolling two-year window. The sample period spans from 1998 to 2024.

	Low	Q2	Q3	Q4	High	High-Low
Sorted by $MELCs$ from Equity Report						
SignedCAR[0, +1]	−0.18	−0.18	0.12	0.15	0.07	0.25
	(−2.13)	(−1.60)	(1.68)	(2.10)	(0.96)	(2.39)
SignedCAR[0, +2]	−0.17	−0.17	0.08	0.12	0.03	0.20
	(−2.05)	(−1.39)	(1.08)	(1.58)	(0.40)	(1.90)
SignedCAR[0, +3]	−0.18	−0.19	0.08	0.12	0.04	0.22
	(−2.08)	(−1.53)	(1.03)	(1.44)	(0.53)	(1.99)

Table 12: Forecast Error by Valuation Method

This table presents regression results analyzing the effect of macro-equity logic chains on analyst forecast errors, conditional on valuation method employed in the report. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the previous four years. The key explanatory variable, *Logic*, is an indicator equal to one if the forecast is associated with an equity report containing a macro-equity logic chain of the specific type shown in the column headers, and zero otherwise. We randomly select 10% of all earnings forecasts and utilize LLMs to identify the valuation methods employed by analysts in their reports. Column (1) reports results for all forecasts matched to our randomly selected reports. Column (2) presents results for forecasts associated with Price-to-Earnings valuation methods. Column (3) presents results for forecasts associated with all multiple-based valuation methods (including P/E, P/B, etc.), while Column (4) reports results for forecasts associated with discounted cash flow models and other non-multiple valuation approaches. All specifications control for firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Absolute Error / Std Past Error			
	(1)	(2)	(3)	(4)
Valuation Method	Full Sample	P/E	Any Multiples	DCF & Other Non-Multiples
Logic	-33.260**	-32.623**	-39.384***	-36.954**
	(-2.36)	(-2.13)	(-2.77)	(-2.00)
Size	66.932***	49.860***	67.543***	105.898***
	(4.26)	(2.80)	(4.03)	(5.30)
BM	32.700	60.344**	31.959	48.049*
	(1.64)	(2.47)	(1.51)	(1.94)
Mom	-0.067	0.240	0.018	-0.216
	(-0.42)	(1.32)	(0.11)	(-0.87)
Volatility	4.106***	5.472***	3.947***	3.858***
	(3.59)	(3.95)	(3.23)	(2.61)
Profitability	3.137***	5.148***	3.537***	0.442
	(3.18)	(4.06)	(3.50)	(0.38)
LnAge	-332.503***	-311.253***	-326.436***	-352.300***
	(-10.10)	(-8.27)	(-9.40)	(-7.93)
Adjusted R-Squared	0.201	0.198	0.198	0.206
N	118,554	85,553	103,202	54,876
Analyst FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Fiscal Year FE	YES	YES	YES	YES

APPENDIX

A Data Collection of Analyst Reports

A.1 Downloading Analyst Reports

We obtain our sample of analyst reports from Investext, an aggregator available through Mergent Online. Investext provides PDF versions of each report along with comprehensive metadata, including report release date, title, author (sell-side analysts), contributor (brokerage houses or investment banks), covered company names and tickers, and Investext's internal classifications for report style, category, and subject. We download all reports published from January 1, 1998, through December 31, 2024, applying the following filters: `Language=English`, `Region=North America`, and `Country=United States`.

Our macro report sample includes reports with Investext internal labels of `Report Style=Economic Reports` or `Commodity Research`, or `Category=Economics` or `Commodities`. Our equity report sample includes reports with Investext internal labels of `Report Style=Equity` or `Company (Equity) Reports`, or `Category=Equity`. In total, we have 254,752 macro reports and 5,124,799 equity reports.

A.2 Parsing Textual Information

We convert all reports from PDF to plain text using MinerU. MinerU is an open-source algorithm that specializes in extracting textual information from PDF documents. It employs a two-stage extraction approach: first attempting to read text directly from the PDF structure, and when this is not available, utilizing Optical Character Recognition (OCR) to recognize text from scanned documents.

MinerU offers several key advantages for financial document processing: (1) it can distinguish between titles and normal text, preserving hierarchical document structure; (2) it accurately identifies paragraph boundaries, maintaining the logical flow of analytical arguments; and (3) it differentiates tables from surrounding text, ensuring that tabular data is properly segmented. These structural preservation capabilities are essential for our analysis, as they enable us to accurately reconstruct analysts' reasoning patterns and mental models from the original document organization.

Finally, to ensure clean textual data, we remove standardized disclaimer sections by identifying and excluding content with headings such as "Legal Disclaimers" and "Important Disclosures" that commonly appear in analyst reports.

A.3 Matching Equity Reports to IBES

A.3.1 Matching Investext Brokers

We begin by matching Investext's `Contributor` field to IBES brokerage houses. First, we collect all available broker identifiers from the IBES database: `estimid` from the price target file and recommendation file, and `emaskcd` from the detail forecast file. We then obtain the full names of IBES brokerage houses corresponding to each broker ID using IBES broker-analyst file. Next, we manually verify the brokerage names to address two issues: (1) missing broker names, and (2) name updates resulting from broker mergers and acquisitions. Finally, we match the IBES brokerage names to Investext's `Contributor` field using exact string matching. In total, we successfully match 388 broker identifiers (`emaskcd`) from IBES.

A.3.2 Matching Investext Analysts

We next match Investext's `Author` field to IBES analysts. We first collect all available analyst identifiers from the IBES database: `amaskcd` from the price target file and recommendation file, and `analys` from the detail forecast file. We then clean the prefixes (e.g., "Ms.", "Dr.") and suffix (e.g., "CFA", "Jr.") from analyst names and extract the first name and last name initial for each analyst identifier. For demographic information, we use Python packages `gender_guesser`[5] and `pyethnicity`[6] to predict each analyst's gender and race using their first name and last name. We match IBES analysts to Investext's `Author` field using exact matching on first name and last name initial, with the additional requirement that the Investext `Contributor` must exactly match the IBES brokerage name identified in the previous subsection. When an Investext analyst record matches multiple IBES analyst records, we require that the report release date falls within the analyst's tenure at that particular brokerage according to the IBES database. In total, we successfully match

[5] `gender_guesser` matches first names to a gender based on a library, which contains over 40,000 first names from several countries.

[6] `pyethnicity` uses 2022 voter registration data to train a model that predicts race from names.

9,786 analyst identifiers (amaskcd) from IBES.

A.3.3 Matching Investext Companies

We next match Investext companies to our public finance database. We begin by constructing a comprehensive firm identifier dataset at the permno-ticker-name-date level using two primary sources: dsenames from CRSP and ibcrsphist from WRDS. We then extract covered firm information from Investext using a hierarchical matching approach. First, we check whether the report Title begins with or contains any firm ticker. For reports where ticker matching is unsuccessful, we examine the Tickers field for company CUSIPs and tickers. Finally, we perform exact string matching on the Company Names field for any remaining unmatched reports. This sequential matching strategy ensures maximum coverage while maintaining matching precision. A single report may cover multiple companies. In total, we successfully match 16,763 firm identifiers (permno) across our sample period.

A.3.4 Matching Report with Forecast Record

Finally, we match our analyst reports to earnings forecast records from IBES. We begin by extracting all earnings forecasts with fpi=1 from the IBES detu_epsus unadjusted detail history file. Each forecast record contains information about the broker, analyst, company, announcement date (anndats), and review date (revdats). The announcement date represents when an analyst revises her estimate and issues a forecast, while the review date indicates when an analyst confirms to IBES that her outstanding forecast remains current. To ensure date alignment between reports and forecasts, we require that the report release date falls within a window spanning from two days before the announcement date to two days after the review date.

We then match reports to forecasts using four criteria: (1) broker identity, (2) analyst identity, (3) company identification, and (4) the date window described above. This comprehensive matching approach ensures that we accurately link published reports with their corresponding earnings forecasts. In total, we successfully match 1,196,519 earnings forecasts from IBES.

J.P.Morgan

North America Equity Research
11 February 2016

Axalta Coating Systems Ltd.

We Trim Estimates

Neutral

AXTA, AXTA US
Price: $23.58

▼ **Price Target: $26.00**
Previous: $29.00

The larger issue in purchasing Axalta, or any coatings company with substantial exposure to the auto OEM sector, is the earnings risk assumed in the event of an economic downturn. Under such circumstances, there would be a sharp volume contraction for a period of time as auto production resets downwards. Axalta's trading multiples are likely to fluctuate with economic sentiment over a shorter period of time for this reason. There are also near-term issues. Axalta has indicated market share gains across its business partners, but it is probably the case that core volume growth should be diminished to a degree by demand weakness at its largest customer, Volkswagen. Axalta continues to indicate 4-6% local currency growth for its businesses in 2016, but acquisition effects will now contribute about 1% of that 4-6% year-ahead growth. We note that the company will compare itself to 6-7% light vehicle coatings volume growth in the first half of 2016. Stock compensation expense, which AXTA excludes from its adjusted EBITDA, is now $40m for 2016 versus $8m in 2014. Axalta's accounting detail could be more complete, in our opinion. There is a relatively large gap between adjusted EBITDA and reported EBITDA at Axalta ($201.8m in 2015 and $277.3m in 2014). Axalta does not allocate the components of these differences either to its individual business segments or to corporate expense, nor does it allocate the components to line items on the consolidated income statement. Of course, educated guesses can be made for allocations, but it would be helpful to know, for example, the adjusted cost of goods sold when quarterly earnings are reported. It is also the case that there is not sufficient information to connect balance sheet changes with funds flow changes in the company's most recent press release. The working capital use for 2015 for Axalta was ($191.1m). But from simply examining the change in receivables, inventories, and payables, it would appear that that there was little working capital use. Accordingly, there is much captured in the funds flow statement that is not easily derived from the balance sheet. We rate Axalta Neutral for year-ahead performance.

- **We lower our 2016 EBITDA estimate for AXTA from $912m to $859m to reflect $40m in stock comp. expense** (prev. forecast $6m) and lower expectations for Performance margins stemming from negative pricing in Industrial Coatings as well as a moderation in growth rate. We think Axalta will throw off 6.7% of its share price in free cash flow in 2016, which we find attractive. We believe, however, that the free cash flow generation for PPG is comparable (excl. asbestos settlement costs) as are the trading multiples. PPG has less financial leverage (1.2x 2016E EBITDA) versus AXTA (3.0x). Both investments are appealing, but we prefer PPG.

Chemicals: Specialty, Commodity and Agricultural

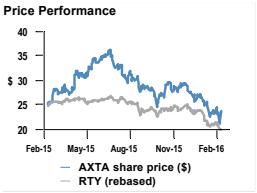
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Price Performance



	YTD	1m	3m	12m
Abs	-8.7%	-5.4%	-16.5%	-5.6%
Rel	4.4%	2.5%	2.4%	14.3%

Axalta Coating Systems Ltd. (AXTA;AXTA US)

FYE Dec	2015A	2016E (Prev)	2016E (Curr)	2017E (Prev)	2017E (Curr)	2018E
EPS - Recurring ($)						
Q1 (Mar)	0.16	-	0.17	-	-	-
Q2 (Jun)	0.33	-	0.36	-	-	-
Q3 (Sep)	0.27	-	0.29	-	-	-
Q4 (Dec)	0.24	-	0.23	-	-	-
FY	1.00	1.25	1.05	1.50	1.25	1.45
Bloomberg EPS FY ($)	1.06	-	1.30	-	1.57	1.90

Source: Company data, Bloomberg, J.P. Morgan estimates.

Company Data	
Price ($)	23.58
Date Of Price	10 Feb 16
52-week Range ($)	36.50-20.67
Market Cap ($ mn)	5,724.05
Fiscal Year End	Dec
Shares O/S (mn)	243
Price Target ($)	26.00
Price Target End Date	31-Dec-16

See page 19 for analyst certification and important disclosures.

J.P. Morgan does and seeks to do business with companies covered in its research reports. As a result, investors should be aware that the firm may have a conflict of interest that could affect the objectivity of this report. Investors should consider this report as only a single factor in making their investment decision.

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Figure A1: Sample Equity Report

Deutsche Bank
Research

North America
United States

Economics
US Daily Economic Notes

Date
22 May 2017

What may Fed reinvestment tapering look like?

Tuesday	Release	Forecast	Previous	Consensus
10:00 AM	New home sales (Apr):	625k	621k	610k
10:00 AM	May Richmond Fed PMI is released			

Source: Deutsche Bank , Bloomberg Finance LP

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Commentary for Tuesday: The FOMC minutes will likely be the main event this week since they are expected to contain an extensive discussion of the Fed's balance sheet strategy. While we do not think that the Committee has reached a clear consensus yet in terms of the specific details, we expect a broad outline to begin to emerge in terms of general timing and operating principles. In the following commentary, we provide our "House View" of what balance sheet normalization may look like.

We see the Fed hiking two more times this year in June and September. The Fed is then expected to pause in December to announce the tapering of its balance sheet, beginning in January of next year. The Fed would like to make this policy change as transparent and simple for the market as possible to limit the extent of any adverse market reaction. As a result, we expect the Fed to give clear guidance about the details of the unwind prior to the December announcement. These details should include: How long the phase out period will be and whether they will reduce purchases in dollar or percentage amounts. A key uncertainty that we do not expect to be clarified in the near-term is the longer-term size of the balance sheet (i.e., the amount of excess reserves necessary to effectively carry out monetary policy).

In general, we believe the tapering of reinvestments may look somewhat similar to the tapering of securities purchases in 2014. Recall that for QE3 the Fed announced in December 2013 that it would cut total asset purchases from $85 billion per month ($45 billion of Treasuries / $40 billion of MBS) to $75 billion in January of 2014. The Fed then announced a $10 billion reduction in asset purchases at each of its next six meetings, and concluded its asset purchase program at the October 29 meeting. This time, we think it will take roughly a year to completely end reinvestments. This more extended timeline is due to the fact that the Committee wants to keep the fed funds rate as the main policy tool and have the balance sheet unwind occur in a passive manner that limits market disruption.

Although we expect the Fed to pause on hiking the funds rate in December, this will likely be the only time that changes in reinvestment policy and the fed funds

Figure A2: Sample Macroeconomic Report

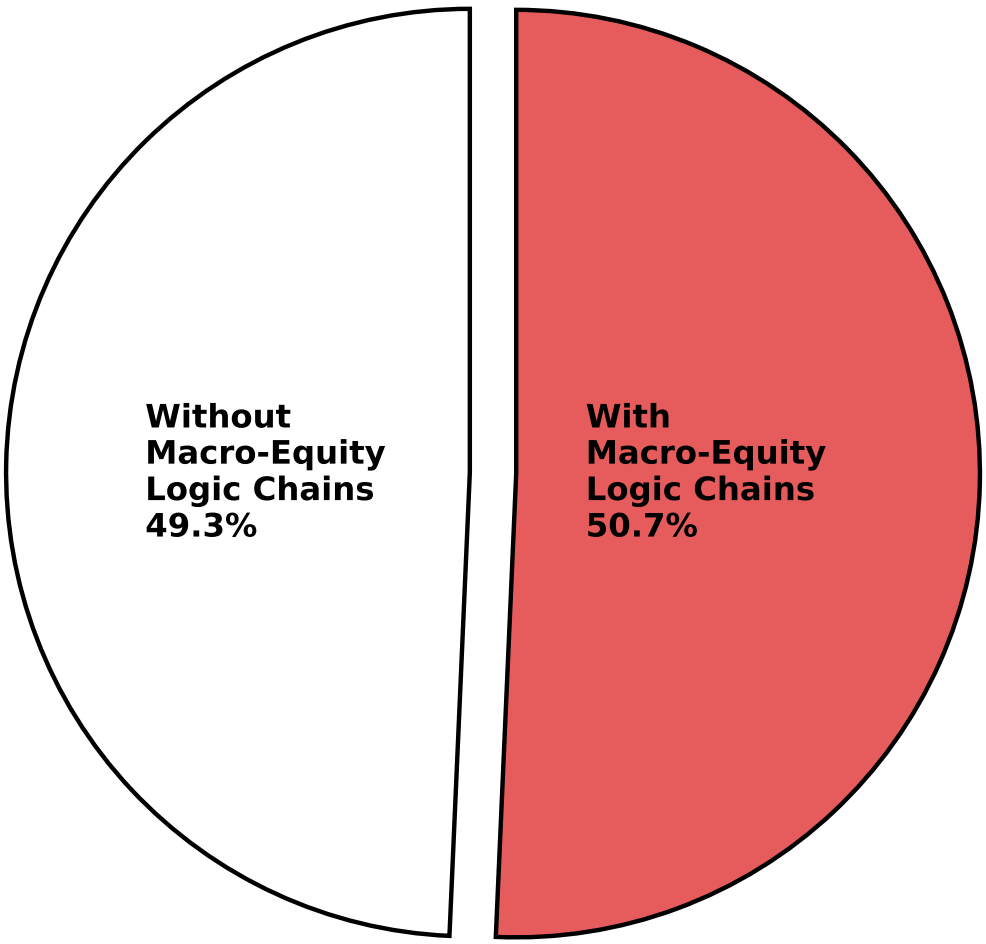


Figure A3: Fraction of Equity Logic Chains in Macro Reports

This figure presents a pie chart that illustrates the proportion of macro reports containing macro-equity logic chains versus those without explicit macro-equity logic chains. Our sample includes macro reports over the period 1998–2024.

Table A1: Performance Evaluation

This table presents the performance evaluation of the llm in terms of extracting macro-equity logic chains, causes, outcome, and cause-outcome categories. We compare the performance of DeepSeek-V3.2-Exp and Gemini-2.5-Flash in terms of accuracy, precision, recall, and F1 against human annotations of a randomly chosen set of 100 MELC-related segments (50 from equity reports and 50 from macro reports). We group our fact-checking into four scenarios. True positive (TP) denotes a scenario in which generative AI extracts similar information about MELC, cause, and effect relations as we do. False positive (FP) denotes a scenario in which generative AI extracts different (false) information from what we do. True negative (TN) denotes a scenario in which generative AI extracts no information and neither do we. False negative (FN) denotes a scenario in which generative AI extracts false information while we do not find relevant information. We compute four performance metrics. Accuracy is defined as (TP + TN)/(TP + FP + TN + FN), and measures how accurate a model is at correctly classifying MELC from the reports. Precision is defined as (TP)/(TP + FP) and measures how accurate a model is at identifying correct (positive) MELC information of all MELC information that is predicted to be positive. Recall is defined as (TP)/(TP + FN), and measures how accurate a model is at identifying correct (positive) MELC information of all identified MELC information. F1 is the harmonic mean of Precision and Recall.

	Report Type	Containing Logic	Cause Category	Effect Category	Cause-Effect
Panel A: Deepseek V3.2 Exp					
Accuracy	Equity	90.00%	84.00%	84.00%	72.00%
	Macro	98.00%	90.00%	86.00%	70.00%
Precision	Equity	90.00%	93.33%	93.33%	80.00%
	Macro	98.00%	91.84%	87.76%	71.43%
Recall	Equity	100.00%	89.36%	89.36%	87.80%
	Macro	100.00%	97.83%	97.73%	97.22%
F1	Equity	94.74%	91.30%	91.30%	83.72%
	Macro	98.99%	94.74%	92.47%	82.35%
Panel B: Gemini 2.5 Flash					
Accuracy	Equity	94.00%	76.00%	78.00%	34.00%
	Macro	100.00%	84.00%	80.00%	56.00%
Precision	Equity	100.00%	84.44%	86.67%	37.78%
	Macro	100.00%	85.71%	81.63%	57.14%
Recall	Equity	93.33%	88.37%	88.64%	77.27%
	Macro	100.00%	97.67%	97.56%	96.55%
F1	Equity	96.55%	86.36%	87.64%	50.75%
	Macro	100.00%	91.30%	88.89%	71.79%

Table A2: Forecast Error From Report With and Without Macro-Equity Logic Chain – Industry $\times$ Year Fixed Effects

This table presents regression results analyzing the effect of macro-equity logic chains on analyst forecast errors. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the previous four years. The key explanatory variable, *Logic*, is an indicator equal to one if the forecast is associated with an equity report containing a macro-equity logic chain of the specific type shown in the column headers, and zero otherwise. Column (1) reports results for logic chains of any type. Columns (2) through (4) examine chains driven by three specific causes: Commodities & Raw Materials, Domestic Economy, and Monetary Policy. Columns (5) through (7) focus on chains resulting in three specific effects: Equity Valuation, Earnings & Revenue, and Business Operations. All specifications control for firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. We further include industry-by-time fixed effects, where industry is defined according to the Fama-French 48-industry classification. t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

Dependent Variable: Absolute Error / Std Past Error							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any Type	Cause			Effect		
Sample Category		Commodity & Materials	Domestic Economy	Monetary Policy	Equity Valuation	Earnings & Revenue	Business Operations
Logic	-28.649***	-20.360***	-35.831***	-45.819***	-30.370***	-32.640***	-36.798***
	(-6.32)	(-2.73)	(-4.45)	(-6.10)	(-5.76)	(-5.74)	(-4.45)
Size	117.107***	114.892***	110.085***	109.972***	116.410***	111.505***	110.713***
	(16.56)	(15.89)	(14.92)	(14.97)	(16.33)	(15.58)	(15.04)
BM	41.980***	40.716***	39.696***	36.669***	42.728***	38.001***	40.287***
	(4.46)	(4.21)	(3.95)	(3.66)	(4.49)	(3.92)	(4.06)
Mom	-0.404***	-0.381***	-0.410***	-0.410***	-0.381***	-0.416***	-0.390***
	(-6.83)	(-6.34)	(-6.74)	(-6.73)	(-6.40)	(-6.98)	(-6.38)
Volatility	0.812*	1.041**	0.834*	1.006**	1.031**	1.021**	1.061**
	(1.76)	(2.16)	(1.69)	(2.06)	(2.20)	(2.13)	(2.16)
Profitability	3.539***	3.508***	3.918***	3.873***	3.537***	3.724***	3.824***
	(8.68)	(8.56)	(9.21)	(9.16)	(8.64)	(9.05)	(9.10)
LnAge	-440.234***	-447.616***	-447.035***	-444.562***	-446.619***	-440.209***	-447.917***
	(-27.14)	(-26.14)	(-25.46)	(-25.19)	(-27.09)	(-26.09)	(-25.46)
Adjusted R-Squared	0.239	0.239	0.242	0.240	0.239	0.238	0.241
N	993,894	846,856	823,034	823,264	925,784	888,176	809,384
Analyst FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Industry × Fiscal Year FE	YES	YES	YES	YES	YES	YES	YES

Table A3: Forecast Error From Report With and Without Macro-Equity Logic Chain: Controlling for Macro Word

This table extends the analysis in Table 5 by including the variable *Macro Word* as an additional control. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the previous four years. The key explanatory variable, *Logic*, is an indicator equal to one if the forecast is associated with an equity report containing a macro-equity logic chain of the specific type shown in the column headers, and zero otherwise. Column (1) reports results for logic chains of any type. Columns (2) through (4) examine chains driven by three specific causes: Commodities & Raw Materials, Domestic Economy, and Monetary Policy. Columns (5) through (7) focus on chains resulting in three specific effects: Equity Valuation, Earnings & Revenue, and Business Operations. All specifications control for firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

Dependent Variable: Absolute Error / Std Past Error							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any Type	Cause			Effect		
Sample Category		Commodity & Materials	Domestic Economy	Monetary Policy	Equity Valuation	Earnings & Revenue	Business Operations
Logic	-15.941***	-21.010**	-24.286**	-28.425***	-18.032***	-16.727**	-25.464***
	(-2.88)	(-2.53)	(-2.57)	(-3.32)	(-2.80)	(-2.56)	(-2.62)
Macro Word	-35.077***	-34.309***	-34.391***	-35.563***	-32.930***	-35.515***	-35.041***
	(-6.68)	(-6.35)	(-6.42)	(-6.62)	(-6.15)	(-6.69)	(-6.47)
Size	118.444***	115.434***	112.595***	112.423***	117.932***	114.516***	112.511***
	(17.85)	(17.36)	(16.23)	(16.31)	(17.54)	(17.09)	(16.42)
BM	40.224***	40.604***	45.486***	43.449***	42.495***	39.729***	45.701***
	(4.11)	(4.16)	(4.44)	(4.28)	(4.30)	(4.03)	(4.54)
Mom	-0.448***	-0.450***	-0.517***	-0.516***	-0.472***	-0.504***	-0.498***
	(-7.47)	(-7.45)	(-8.67)	(-8.61)	(-7.83)	(-8.44)	(-8.29)
Volatility	2.570***	2.798***	2.861***	2.939***	2.701***	2.828***	2.945***
	(5.86)	(6.17)	(6.19)	(6.43)	(6.06)	(6.27)	(6.40)
Profitability	3.865***	3.739***	4.135***	4.059***	3.881***	4.004***	4.015***
	(10.21)	(9.88)	(10.32)	(10.34)	(10.15)	(10.39)	(10.24)
LnAge	-413.892***	-419.750***	-424.994***	-423.967***	-417.501***	-415.031***	-425.283***
	(-27.49)	(-26.37)	(-26.26)	(-26.14)	(-27.13)	(-26.63)	(-26.25)
Adjusted R-Squared	0.179	0.182	0.183	0.182	0.181	0.180	0.183
N	1,054,256	905,063	881,843	879,721	980,347	946,266	868,448
Analyst FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Fiscal Year FE	YES	YES	YES	YES	YES	YES	YES

Table A4: Persistence of Analysts' Attention to Macroeconomic Information in Equity Report

This table examines the persistence in the adoption of macro-equity logic chains within equity reports. The dependent variable is a dummy variable that equals one if an analyst writes an equity report containing a macro-equity logic chain in month t. The independent variable is a dummy variable that equals one if the analyst wrote an equity report containing a macro-equity logic chain in month $t-1$, $t-2$, or $t-3$. Columns (1) through (3) report results for macro-equity logic chain adoption at the analyst level, while Columns (4) through (6) present results at the analyst-firm level. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Analyst Level			Analyst-Firm Level		
Logic Lag 1	23.353***			29.113***		
	(50.92)			(64.66)		
Logic Lag 2		18.099***			25.038***	
		(38.98)			(55.03)	
Logic Lag 3			14.239***			21.700***
			(31.24)			(47.07)
Adjusted R-Squared	0.415	0.403	0.397	0.370	0.354	0.339
N	167,904	157,587	148,296	2,494,501	2,208,431	1,962,185
Analyst FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES	YES

Table A5: Persistence of Analysts' Attention to Macroeconomic Information in Macro Report

This table examines the persistence in the adoption of macro-equity logic chains within macroeconomic reports at the analyst level. The dependent variable is a dummy variable that equals one if an analyst writes a macroeconomic report containing a macro-equity logic chain in month t. The independent variable is a dummy variable that equals one if the analyst wrote a macroeconomic report containing a macro-equity logic chain in month $t-1$, $t-2$, or $t-3$. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic		
	(1)	(2)	(3)
Macro Equity Logic Lag 1	10.136***		
	(7.47)		
Macro Equity Logic Lag 2		5.053***	
		(3.58)	
Macro Equity Logic Lag 3			3.805***
			(2.78)
Adjusted R-Squared	0.295	0.294	0.284
N	23,634	21,476	19,643
Analyst FE	YES	YES	YES

Table A6: Fixed Effects Decomposition in Macro Report

This table presents the results of a fixed effects expectation with macro-equity logic dummy as the main dependent variable. Each cell entry presents the adjusted R-squared from the regression specifications above based on the fixed effects indicated on the left: Time, Analyst, and Time $\times$ Analyst.

Sample Category	(1) Time	(2) Analyst	(3) Time $\times$ Analyst
All Macro $\rightarrow$ All Equity	2.7	13.2	17.7
Commodity & Materials $\rightarrow$ Equity Valuation	1.8	11.3	15.2
Commodity & Materials $\rightarrow$ Earnings & Revenue	1.3	9.6	13.5
Commodity & Materials $\rightarrow$ Business Operations	0.3	3.2	5.4
Domestic Economy $\rightarrow$ Equity Valuation	0.7	7.1	11.1
Domestic Economy $\rightarrow$ Earnings & Revenue	0.4	6.9	11.4
Domestic Economy $\rightarrow$ Business Operations	0.2	4.9	8.7
Monetary Policy $\rightarrow$ Equity Valuation	0.8	7.0	10.6
Monetary Policy $\rightarrow$ Earnings & Revenue	0.4	10.2	13.9
Monetary Policy $\rightarrow$ Business Operations	0.2	3.5	7.1

Table A7: Analysts' Adoption of Macro-Equity Logic Chains: Linking to Analyst and Firm Characteristics

This table examines the determinants of analysts' adoption of macro-equity logic chains in equity reports. The dependent variable, *Logic*, is an indicator variable equal to one if an equity report contains any type of macro-equity logic chain, and zero otherwise. The explanatory variables include a set of analyst characteristics and firm characteristics. *Total tenure* is the log number of years since an analyst first appears in the sample. *Male* is an indicator variable equal to one for a male analyst. *White* is an indicator variable equal to one for an analyst of white race. *Size* is the natural logarithm of market capitalization. *BM* denotes the book-to-market ratio. *Mom* is the cumulative excess return from month $t-12$ to $t-2$. *Profitability* is calculated as EBITDA scaled by total assets. *LnAge* is the natural logarithm of firm age in months. *Word Count* is the natural logarithm of the total number of words in a report. For reports covering multiple firms, firm characteristics are calculated as the market-capitalization-weighted average. T-statistics, reported in parentheses, are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic			
	(1)	(2)	(3)	(4)
Total Tenure	0.110	0.090	-0.149	-0.308
	(0.43)	(0.32)	(-0.59)	(-0.87)
Male	0.943	0.834	0.530	
	(1.36)	(1.21)	(0.85)	
White	0.631	0.750	0.647	
	(0.96)	(1.14)	(1.06)	
Size	0.109	0.279***	0.133*	0.480***
	(1.38)	(3.30)	(1.74)	(9.71)
BM	4.959***	4.752***	3.691***	0.598***
	(19.34)	(18.63)	(15.00)	(4.93)
Mom	0.007***	0.009***	0.008***	-0.001
	(5.08)	(5.81)	(5.75)	(-1.44)
Volatility	-0.015	0.082***	0.086***	0.006
	(-0.83)	(4.24)	(4.64)	(0.88)
Profitability	0.074***	0.061***	0.046***	-0.011**
	(9.43)	(7.35)	(5.64)	(-2.55)
LnAge	1.683***	1.628***	1.394***	0.204**
	(11.45)	(11.05)	(9.92)	(2.55)
Word Count	8.656***	8.634***	7.840***	7.758***
	(32.64)	(33.47)	(44.09)	(46.88)
Adjusted R-Squared	0.077	0.083	0.119	0.253
N	3,782,035	3,782,035	3,782,027	3,781,722
Year FE	NO	YES	YES	YES
Broker FE	NO	NO	YES	YES
Analyst FE	NO	NO	NO	YES

Table A8: Lead Analyst vs. Non-Lead Analyst

This table presents regression results examining how participation in writing macroeconomic reports containing macro-equity logic chains differentially affects lead and non-lead authors' future use of such logic in equity reports. The dependent variable, *Logic*, is an indicator variable that equals one if an equity report contains macroeconomic keywords and zero otherwise. $Exp^{Indicator}\,(Lead)$ is a dummy variable that equals one if an analyst participated as the lead author in writing macroeconomic reports containing macro-equity logic chains over the past two years. $Exp^{Indicator}\,(NonLead)$ is a dummy variable that equals one if an analyst participated as a non-lead author in writing such macroeconomic reports over the past two years. $Exp^{Weighted}\,(Lead)$ and $Exp^{Weighted}\,(NonLead)$ capture the weighted average of such exposure as lead or non-lead authors across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. *Word Count* is the natural logarithm of the total words in a report. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic					
	(1)	(2)	(3)	(4)	(5)	(6)
$Exp^{Indicator}\,(Lead)$	0.414**		0.344**			
	(2.52)		(2.11)			
$Exp^{Indicator}\,(NonLead)$		1.067***	1.040***			
		(5.27)	(5.15)			
$Exp^{Weighted}\,(Lead)$				1.429		1.019
				(1.63)		(1.19)
$Exp^{Weighted}\,(NonLead)$					3.519***	3.391***
					(3.85)	(3.72)
Word Count	6.823***	6.821***	6.822***	6.824***	6.822***	6.822***
	(45.61)	(45.64)	(45.66)	(45.61)	(45.56)	(45.57)
Adjusted R-Squared	0.251	0.251	0.251	0.251	0.251	0.251
N	6,222,950	6,222,950	6,222,950	6,222,950	6,222,950	6,222,950
Year FE	YES	YES	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES

Table A9: Adoption of Macro-Equity Logic Chains: Analysts with Few Experiences in Writing Macro Reports

This table examines how analysts' past exposure to macro-equity logic chains through participation in writing macroeconomic reports influences their future adoption of such logic chains in equity reports. We focus on a subsample of analysts with rare experience in writing macro reports. The dependent variable, *Logic*, is a binary indicator equal to one if an equity report contains any type of macro-equity logic chain and zero otherwise. The key explanatory variable, $Exp^{Weighted}$, represents the weighted average of an analyst's exposure to writing macro reports across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. *Word Count* is the natural logarithm of the total words in a report. Column (1) examines a subsample of analysts with a low frequency of writing macro reports (below the population mean frequency). Column (2) focuses on a subsample of analysts with a low number of macro reports (below the population mean number). Column (3) builds on Column (2) and further restricts the sample to analysts whose average time gap between consecutive macro reports is above the population median. Column (4) also builds on Column (2) but restricts the sample to analysts who do not serve as the lead analyst in any of the macro reports they wrote. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic			
	(1)	(2)	(3)	(4)
	Low Frequency	Low Number	Low Number & Long Gap	Low Number & Non-Lead
$Exp^{Weighted}$	2.319***	2.952***	1.846**	3.183**
	(2.76)	(4.31)	(2.15)	(2.57)
Word Count	6.682***	6.889***	6.548***	6.626***
	(35.68)	(41.33)	(30.19)	(25.63)
Adjusted R-Squared	0.190	0.215	0.164	0.231
N	3,794,683	3,853,634	2,074,482	731,464
Year FE	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES

Table A10: Adoption of Macro-Equity Logic Chains: Past Experiences during High Economic Uncertainty

This table examines how analysts' past exposure to macro-equity logic chains through participation in writing macroeconomic reports influences their future adoption of such logic chains in equity reports. The analysis focuses on episodes of high economic uncertainty, which are likely periods when brokers face constraints in writing macro reports. The dependent variable, *Logic*, is a binary indicator equal to one if an equity report contains any type of macro-equity logic chain and zero otherwise. The key explanatory variables capture analysts' prior exposure to macro-equity logic chains during high economic uncertainty. In Column (1), $Exp^{Indicator}\,(High\,EPU)$ is a dummy variable equal to one if an analyst participated in writing macroeconomic reports containing macro-equity logic chains during high economic uncertainty over the past two years. In Column (2), $Exp^{Weighted}\,(High\,EPU)$ represents the weighted average of such exposure during high economic uncertainty across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. Column (3) builds on Column (1), where $Exp^{Indicator}\,(High\,EPU,\,NonLead)$ is a dummy variable equal to one if the analyst did not serve as the lead analyst when writing macro reports during episodes of high economic uncertainty. Column (4) builds on Column (3), with $Exp^{Weighted}\,(High\,EPU,\,NonLead)$ capturing the weighted average of such exposure across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. *Word Count* is the natural logarithm of the total words in a report. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Macro-Equity Logic			
	(1)	(2)	(3)	(4)
$Exp^{Indicator}\,(High\,EPU)$	0.777***			
	(5.61)			
$Exp^{Weighted}\,(High\,EPU)$		2.726***		
		(3.82)		
$Exp^{Indicator}\,(High\,EPU,\,NonLead)$			1.054***	
			(5.23)	
$Exp^{Weighted}\,(High\,EPU,\,NonLead)$				3.310***
				(3.48)
Word Count	6.824***	6.825***	6.822***	6.824***
	(45.62)	(45.59)	(45.64)	(45.58)
Adjusted R-Squared	0.251	0.251	0.251	0.251
N	6,222,950	6,222,950	6,222,950	6,222,950
Year FE	YES	YES	YES	YES
Broker FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES

Table A11: Stacked-DID Regression

This table presents stacked difference-in-differences (DID) regression results analyzing analysts' attention to macroeconomic information. The analysis is conducted at the analyst-month level. Columns (1) and (2) estimate the effect within a $[-2, +2]$ month window of the analyst's first experience of macro-equity logic, while Columns (3) and (4) use a $[-3, +3]$ month window. The dependent variable is an indicator that equals one if an analyst issued at least one equity report containing macro-equity logic chains in a given month. *Treat* is an indicator that equals one for analysts with experience related to macro-equity logic chains. *Post* equals one for months on or after the month of this initial experience, and zero for months preceding it. *Report Number* is the log number of reports an analyst issued in a month. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1983 to 2024. All coefficients are multiplied by 100.

	Equity Report with Macro-Equity Logic			
	(1)	(2)	(3)	(4)
Cohort Window	$[-2, +2]$	$[-2, +2]$	$[-3, +3]$	$[-3, +3]$
Treat × Post	1.669**	1.402**	1.484**	1.303**
	(2.34)	(1.97)	(2.26)	(1.99)
Treat	18.612***	2.460***	17.526***	2.367***
	(20.66)	(3.49)	(19.46)	(3.46)
Report Number	11.922***	15.122***	12.391***	15.284***
	(27.07)	(47.33)	(25.69)	(44.84)
Adjusted R-Squared	0.081	0.361	0.081	0.363
N	946,770	946,770	1,162,140	1,162,140
Cohort × Time FE	YES	YES	YES	YES
Analyst FE	NO	YES	NO	YES

Table A12: Unconditional Forecast Error

This table presents regression results examining analysts' forecast accuracy at the individual forecast level. The dependent variable is the absolute forecast error, scaled by the standard deviation of the absolute consensus forecast errors over the previous four years. The key explanatory variables capture analysts' prior exposure to macro-equity logic chains. $Exp^{Indicator}$ is a dummy variable that equals one if an analyst participated in writing macroeconomic reports containing macro-equity logic chains over the past two years. $Exp^{Weighted}$ captures the weighted average of such exposure across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure. Controls include firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. The t-statistics in parentheses are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

	Dependent Variable: Absolute Error / Std Past Error			
	(1)	(2)	(3)	(4)
$Exp^{Indicator}$	-29.366***	-16.271***		
	(-3.79)	(-5.19)		
$Exp^{Weighted}$			-167.747***	-88.451***
			(-5.59)	(-7.45)
Size	139.759***	111.113***	139.863***	111.156***
	(30.72)	(10.41)	(30.77)	(10.42)
BM	49.887***	-129.635***	50.572***	-129.603***
	(8.69)	(-17.58)	(8.84)	(-17.57)
Mom	-0.553***	0.026	-0.554***	0.025
	(-12.91)	(0.70)	(-12.96)	(0.69)
Volatility	3.004***	-5.606***	3.033***	-5.608***
	(9.31)	(-18.93)	(9.40)	(-18.94)
Profitability	4.123***	0.989***	4.090***	0.988***
	(14.79)	(3.21)	(14.67)	(3.21)
LnAge	-414.205***	-5.1e+03***	-415.520***	-5.1e+03***
	(-38.90)	(-94.10)	(-39.06)	(-94.10)
Adjusted R-Squared	0.182	0.669	0.182	0.669
N	2,337,137	2,334,926	2,337,137	2,334,926
Analyst FE	YES	YES	YES	YES
Firm FE	YES	NO	YES	NO
Fiscal Year FE	YES	NO	YES	NO
Firm × Fiscal Year FE	NO	YES	NO	YES

Table A13: Market Impact - Adjusted by DGTW Return

This table examines the influence of macro-equity logic chains on the market impact of analyst stock recommendations. The dependent variable is the signed cumulative abnormal return, measured over a two-, three-, or four-day window beginning on the recommendation date. The signed CAR for a recommendation on stock i is defined as:

$$SignedCAR_i[0,+T] = \text{Sign}(Revision_i) \times \left[\prod_{t=0}^{T} (1 + R_{i,t}) - \prod_{t=0}^{T} (1 + R_{DGTW,t}) \right],$$

where $T+1$ represents the window length, $R_{i,t}$ denotes the raw stock return on day t, and $R_{DGTW,t}$ represents the return of DGTW portfolio matched on size, book-to-market (B/M), and momentum characteristics Daniel et al. (1997) on day t. The key explanatory variable, $MELCs$, captures the frequency with which an analyst adopted macro-equity logic chains in equity reports prior to the focal recommendation. This variable is calculated over the analyst's prior tenure using a quarterly decay factor of 1.125. Control variables include firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. The t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans 1998 to 2024. All coefficients are multiplied by 100.

	SignedCAR$[0,+1]$	SignedCAR$[0,+2]$	SignedCAR$[0,+3]$
	(1)	(2)	(3)
$MELCs$	69.512***	47.426*	30.445
	(2.99)	(1.82)	(1.10)
Size	-32.929***	-37.252***	-42.523***
	(-4.78)	(-4.93)	(-5.52)
BM	1.376	3.374	-2.701
	(0.12)	(0.27)	(-0.20)
Mom	-0.314***	-0.309***	-0.316***
	(-4.00)	(-3.66)	(-3.60)
Volatility	2.032***	1.757***	1.547**
	(3.23)	(2.61)	(2.22)
Profitability	-1.971***	-1.908***	-1.903**
	(-3.39)	(-2.92)	(-2.54)
LnAge	-86.819***	-90.526***	-93.355***
	(-7.48)	(-7.18)	(-7.00)
Adjusted R-Squared	0.231	0.219	0.211
N	162,993	162,993	162,993
Analyst FE	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table A14: Market Impact - Portfolio Sorting Using Experience from Macro Report

This table employs a portfolio sorting approach to evaluate the influence of macro-equity logic chains on the market reaction to analyst stock recommendations. At the end of each month t, recommendations are sorted into quintile portfolios based on the analyst's $MELCs$ value measured from his experience from macro reports. We report the portfolio average signed cumulative buy-and-hold abnormal return (signed CAR) for all recommendations issued in month $t + 1$. The signed CAR is adjusted by subtracting the firm-specific average signed CAR computed over a rolling two-year window. The sample period spans from 1998 to 2024. t-statistics are reported in parentheses.

	Low	Q2	Q3	Q4	High	High-Low
Sorted by $MELCs$ from Macro Report						
SignedCAR[0, +1]	−0.11	−0.06	−0.07	−0.03	0.15	0.26
	(−1.49)	(−0.62)	(−0.90)	(−0.30)	(1.68)	(2.39)
SignedCAR[0, +2]	−0.11	−0.03	−0.05	−0.09	0.13	0.24
	(−1.48)	(−0.27)	(−0.60)	(−0.98)	(1.43)	(2.28)
SignedCAR[0, +3]	−0.11	0.01	−0.07	−0.13	0.15	0.25
	(−1.47)	(0.09)	(−0.73)	(−1.28)	(1.31)	(2.13)

Table A15: Forecast Error and Length of Macro-Equity Logic Chain

This table extends the analysis in Table 5 by studying how the length of the logic chain affects forecast error. The dependent variable is the absolute forecast error, scaled by the standard deviation of absolute consensus forecast errors over the previous four years. The key explanatory variables, *Logic (2 Elements)* and *Logic (> 2 Elements)*, are indicator variables equal to one if a forecast is associated with an equity report containing a macro-equity logic chain of exactly two elements, or more than two elements, respectively. Column (1) reports results for logic chains of any type. Columns (2) through (4) examine chains driven by three specific causes: Commodities & Raw Materials, Domestic Economy, and Monetary Policy. Columns (5) through (7) focus on chains resulting in three specific effects: Equity Valuation, Earnings & Revenue, and Business Operations. All specifications control for firm size, book-to-market ratio, momentum, return volatility, profitability, and firm age. t-statistics (in parentheses) are based on standard errors clustered at the analyst level. The sample period spans from 1998 to 2024. All coefficients are multiplied by 100.

Dependent Variable: Absolute Error / Std Past Error							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Any Type	Cause			Effect		
Sample Category		Commodity & Materials	Domestic Economy	Monetary Policy	Equity Valuation	Earnings & Revenue	Business Operations
Logic (2 Elements)	-33.549***	-52.038***	-79.553***	-51.980**	-27.167**	-33.999**	-68.992***
	(-6.23)	(-2.68)	(-3.03)	(-2.41)	(-2.12)	(-2.49)	(-2.59)
Logic (> 2 Elements)	-15.936***	-11.215	-2.867	-36.185**	-14.083*	-22.669**	-22.918
	(-2.89)	(-1.00)	(-0.18)	(-2.31)	(-1.66)	(-2.44)	(-1.17)
Size	118.769***	115.116***	112.757***	112.563***	118.041***	113.921***	112.661***
	(17.88)	(17.25)	(16.21)	(16.35)	(17.54)	(16.97)	(16.40)
BM	40.796***	41.593***	46.869***	44.965***	43.201***	41.102***	46.868***
	(4.14)	(4.20)	(4.54)	(4.39)	(4.36)	(4.12)	(4.63)
Mom	-0.443***	-0.446***	-0.512***	-0.508***	-0.467***	-0.496***	-0.490***
	(-7.38)	(-7.39)	(-8.57)	(-8.48)	(-7.75)	(-8.33)	(-8.16)
Volatility	2.566***	2.802***	2.870***	2.940***	2.697***	2.851***	2.956***
	(5.84)	(6.15)	(6.18)	(6.40)	(6.03)	(6.29)	(6.39)
Profitability	3.815***	3.712***	4.087***	4.009***	3.809***	3.948***	3.951***
	(10.12)	(9.77)	(10.21)	(10.23)	(10.04)	(10.26)	(10.09)
LnAge	-413.889***	-419.688***	-426.803***	-424.027***	-418.800***	-415.350***	-425.265***
	(-27.44)	(-26.23)	(-26.26)	(-26.02)	(-27.04)	(-26.50)	(-26.10)
Adjusted R-Squared	0.178	0.182	0.183	0.182	0.181	0.180	0.183
N	1,056,240	899,766	877,525	876,054	975,132	938,688	863,571
Analyst FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Fiscal Year FE	YES	YES	YES	YES	YES	YES	YES

Table A16: Variable Definitions

Variable	Definition
Abs Error / Std Past Error	The absolute forecast error scaled by the standard deviation of the absolute consensus forecast errors over the previous four year.
Logic	A binary indicator equal to one if an equity report contains any type of macro-equity logic chain and zero otherwise.
Word Count	The natural logarithm of the total words in a report.
Size	The log of market capitalization.
BM	The ratio of book value of equity to market value of equity. Book equity is defined as shareholders' equity plus deferred taxes and investment tax credit, minus the book value of preferred stock. Market value of equity is obtained from CRSP.
Mom	The cumulative excess return from month $t-12$ to $t-2$.
Volatility	Standard deviation of monthly returns over the past six months.
Profitability	EBITDA scaled by total assets. We obtain the most recent data from the Compustat Annual database.
LnAge	The natural logarithm of firm age in months.
Beta	The market beta, estimated from regressing monthly excess stock returns on the monthly excess market return over the previous one years.
Report Number	The log number of equity reports an analyst issued in a month.
Male	A binary indicator equal to one if the analyst is male.
White	A binary indicator equal to one if the race of the analyst is white.
$Exp^{Indicator}$	A dummy variable that equals one if an analyst participated in writing macroeconomic reports containing macro-equity logic chains over the past two years.
$Exp^{Weighted}$	The weighted average of exposure to macro-equity logic chains through participation in writing macro reports across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure.
$Exp^{Indicator}(NonEquity)$	A dummy variable equal to one if an analyst participated in writing macroeconomic reports that did not contain any macro-equity logic chains over the past two years.
$Exp^{Weighted}(NonEquity)$	The weighted average of exposure to writing macro reports without macro-equity logic chains across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure.
$Exp^{Indicator}(Lead)$	A dummy variable that equals one if an analyst participated as the lead author in writing macroeconomic reports containing macro-equity logic chains over the past two years.
$Exp^{Indicator}(NonLead)$	A dummy variable that equals one if an analyst participated as a non-lead author in writing such macroeconomic reports over the past two years.
$Exp^{Weighted}(Lead)$	The weighted average of macro-equity logic exposure as lead author across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure.

(*Continued*)

Variable	Definition
$Exp^{Weighted}(NonLead)$	The weighted average of macro-equity logic exposure as non-lead author across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure.
$Exp^{Indicator}(HighEPU)$	A dummy variable equal to one if an analyst participated in writing macroeconomic reports containing macro-equity logic chains during high economic uncertainty over the past two years.
$Exp^{Weighted}(HighEPU)$	The weighted average of macro-equity logic exposure during high economic uncertainty across past quarters, calculated using a quarterly decay factor of 1.125 over the analyst's entire tenure.