Migration Fear, Information Access, and Analyst Forecast Accuracy

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Abstract

We document a racial accuracy gap in analyst forecast accuracy linked to societal immigration fears. Using 1.3 million EPS forecasts (1990–2023) and a news-based migration fear measure, we find that a one-standard-deviation increase in fear raises Non-White analysts' absolute forecast errors by $0.04 EPS, with no effect on White peers. Using the 2015–2016 U.S. presidential election as an inflection point in immigration sentiment, we find consistent results. The migration fear penalty is most pronounced in firms with high idiosyncratic volatility and is attenuated under Non-White CEO leadership and sanctuary jurisdictions. These findings suggest that societal tensions reduce private information sharing with minority analysts. Supporting this, we find that Non-White analysts experience a 5.7 percentage point reduction in conference call participation during high-fear periods, which coincides with their increased forecast errors. Overall, anti-immigrant sentiment can impede trust and information flows, with implications for market efficiency and labor market consequences.

Keywords: Migration, immigration, financial analyst, earnings forecasts, earnings announcement, forecast accuracy, discrimination

JEL Classifications: G24, J71
Data Availability: All data used in the study are publicly available

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1 Introduction

Capital markets rely on more than publicly observable filings and realizations. A meaningful share of value-relevant information is transmitted through discretionary, trust-based communication—private conversations, selective access to managers, and the interpretation of qualitative "soft" information. When social tensions elevate out-group suspicion, these informal channels can become segmented: information flows more readily within perceived in-groups and less freely to perceived out-groups. While economics and psychology have long recognized that in-group loyalty and out-group suspicion are persistent features of human interaction (Hamilton, 1964; Bowles, 2009), we know relatively little about how these societal frictions distort the production of financial information. This paper investigates whether an intensification of such social beliefs—specifically, migration fear—creates disparities in the forecasting performance of key information intermediaries, i.e., financial analysts, in capital markets.

Migration fear has emerged as one of the most salient and polarizing narratives in the U.S. economy. In the 2024 presidential election, immigration policy surpassed the economy to become the top issue for voters,[1] driven by concerns regarding employment, national security, and cultural identity (Hainmueller and Hopkins, 2014). Regardless of whether these fears are rooted in empirical data or primed by media narratives (Hirshleifer, 2020), they can create widespread societal biases that simplify the world into "us versus them." If these types of widespread societal biases can pervade into financial markets, they can potentially have an adverse impact on the information sets of important stakeholders who are critical for price discovery.

We examine this friction through the lens of sell-side equity analysts. Analysts provide an ideal setting to test how societal biases shape information production because their primary output—earnings forecasts—is both quantifiable and critically dependent on access. As Brown et al. (2015) document, analysts rely heavily on trusted relationships and communications with firm executives to obtain the private information necessary for accuracy and Huang et al. (2017) show that analysts are able to take such information and process it to reveal new and value-relevant insights to markets. Additional work confirms that management access is central to analyst performance: Green

[1] See Wall Street Journal `https://on.wsj.com/404Melm` and Gallup `https://news.gallup.com/poll/611135/immigration-surges-top-important-problem-list.aspx`.

et al. (2014) show that analysts with conference-hosting relationships produce more accurate and timely forecasts, Bradley et al. (2022) find that analysts who facilitate private roadshows between managers and investors issue more informative research, while Bradley et al. (2024) document similar advantages for analysts who organize site visits. If migration fear alters the willingness of executives to trust and communicate across perceived demographic groups, then minority analysts may be differentially impaired.

Using a sample of 1,360,603 quarterly EPS forecasts issued from 1990 to 2023, we measure the intersection of analyst ethnicity and societal sentiment on immigration. We identify analysts' ethnicity using a machine-learning name classifier and proxy for societal anxiety using the Migration Fear Index (Baker et al., 2016). Our baseline results document a significant penalty for Non-White analysts. A one-standard-deviation increase in migration fear is associated with an additional \$0.04 error in forecasted EPS; expressed in regression units, this represents a 7.86% increase relative to the mean of the price-scaled absolute forecast error (AFE). This effect is robust to entropy-balanced samples, alternative xenophobia measures based on Gallup polling, and falsification tests. To strengthen causal inference, we exploit the 2015 onset of the "Make America Great Again" campaign as a shock to nationalist rhetoric, finding that the accuracy gap between White and Non-White analysts widens significantly in the post-2015 period.

A critical question is *why* migration fear impairs minority analyst accuracy. We draw upon prior work by evolutionary biologists and psychologists (Hamilton, 1964; Bowles, 2009) who document that out-group biases increase skepticism and distrust, and theorize that Non-White analysts will be more likely to be denied access to private information, thereby leading to less accurate forecasts, and that such forecast errors will be moderated by the level of societal migration fear.

Our empirical evidence supports a theory of selective information-provisioning. We employ a series of tests based on the premise that if information access is rooted in trust, the racial disparity in forecast accuracy should attenuate when (1) out-group bias is lower, reducing the baseline for distrust. Conversely, the forecast-accuracy gap between Non-White and White analysts should worsen when (2) earnings forecasts are more sensitive to firm-specific information and (3) Non-White analysts are unable to extract private information from conference calls. Consistent with this, we find the accuracy penalty for minority analysts vanishes entirely when the CEO is also

Non-White or when the firm is headquartered in a "Sanctuary" jurisdiction. Furthermore, the effect is concentrated in firms with high idiosyncratic volatility—where firm-specific information is most valuable—and is significantly larger when minority analysts are excluded from earnings conference calls.

Having documented evidence consistent with a Migration Fear penalty for minority analysts, we examine their forecasting behavior during periods of elevated migration fear and find that minority analysts often respond to these conditions by exhibiting increased levels of herding behavior: they are more likely to revise toward consensus and issue last-minute revisions—patterns consistent with reduced confidence in their private information.

Finally, we conduct additional tests to examine alternative explanations that operate through analysts' limited information processing rather than information access. One possibility is that elevated migration fear induces distraction or reduced processing capacity among minority analysts, in which case the effect should be strongest when analysts face binding resource constraints, such as smaller brokerages or heavier coverage portfolios. We find no evidence of such heterogeneity. A second possibility is that migration fear induces pessimistic bias in minority analysts' forecasts, potentially reflecting mood or affective responses rather than information frictions. We test this implication directly and are unable to find any evidence of systematic directional bias. Our baseline results are further robust to entropy-balanced samples and to a wide range of alternative specifications for analyst forecast error, migration fear, and controls for macroeconomic and trade policy uncertainty. Taken together, these analyses provide no support for these alternative explanations and instead align with the notion that the migration fear penalty operates primarily through differential access to firm-specific information.

Our findings contribute to a new intellectual paradigm of social economics and finance in which social beliefs can impact economic outcomes (Hirshleifer, 2020). Primarily, we show that migration fears can manifest in society-wide race-related biases that pervade into capital markets' information production. We find that migration fears create disparities in private information flows whereby Non-White analysts receive less access to private information, ultimately resulting in lower forecast accuracy. Our findings suggest that society-wide migration fear can negatively affect the career opportunities of Non-White analysts and may also hinder the price discovery process as a result of elevated analyst disagreement. In addition, we contribute to a rapidly growing body of literature on culture and diversity in financial markets.[2]

The remainder of our paper is structured as follows. Section 2 motivates the research setting. Section 3 discusses empirical design. Section 4 details the construction of the sample. Section 5 presents sample statistics and the main findings from baseline regressions. Section 6 addresses causal inference. Section 7 provides further evidence of our proposed theory with cross-section analyses and tests of information access frictions. Section 8 examines robustness. Section 9 concludes.

2 Motivation

On earnings announcement days and throughout the fiscal quarter, analysts gather information from various channels—public filings, industry data, and critically, private communications with firm executives—to produce accurate EPS forecasts. Brown et al. (2015) document that confidential discussions with management represent a primary source of private information for sell-side analysts, making access to executives essential for forecast accuracy.

Yet information acquisition is not costless (Grossman and Stiglitz, 1980), and information exchange requires trust, particularly when one party faces legal or reputational risk from disclosure.[3] Research across a wide variety of disciplines has shown that societal divisions—whether rooted in race, ethnicity, or political beliefs—can erode interpersonal trust and impede information flows.[4]. Evolutionary biologists and psychologists argue that in-group loyalty and out-group suspicion persist as automatic reactions even in modern society (Hamilton (1964), Trivers (1971)). Similarly, Hirshleifer (2020) suggests that emotionally charged narratives—such as migration fears—can amplify "folk models" that simplify the world into 'us versus them,' distorting social norms around trust and cooperation.

Our study builds on this logic but focuses on a different margin: how societal migration fears may compromise minority analysts' access to private information from firm executives. Executives

[2] A partial list includes Brochet et al. (2016), Rupar et al. (2024), Brochet et al. (2019), Merkley et al. (2020), and Flam et al. (2023).

[3] See, e.g., Akerlof and Kranton (2005); Fershtman and Gneezy (2001);Barr et al. (2018).

[4] Examples include Tyler (2005) on law enforcement; Iyengar and Westwood (2015) on political polarization; Alsan et al. (2019) on healthcare; Lelkes et al. (2017)

sharing private information with analysts face potential liability under Regulation FD, making trust especially salient in this context. Peng et al. (2022) show that analysts perceived as more trustworthy enjoy better access to private information, and Even-Tov et al. (2023) document that incidental similarities, such as sharing the same first name between CEOs and analysts, facilitate information sharing. A growing body of evidence confirms that discretionary management access remains a primary driver of analyst performance in the post-Regulation FD era: Green et al. (2014) find that conference-hosting relationships improve forecast accuracy and timeliness, while Bradley et al. (2022, 2024) show that analysts who facilitate private roadshows and site visits produce more informative research. Because the overwhelming majority of CEOs in our sample are White (approximately 95%), migration fears may manifest as broader race-related biases that strengthen in-group preferences, limiting private information access for Non-White analysts and ultimately degrading their forecast accuracy.Because the overwhelming majority of CEOs in our sample are White (approximately 95%), migration fears may manifest as broader race-related biases that strengthen in-group preferences, limiting private information access for Non-White analysts and ultimately degrading their forecast accuracy.

An important conceptual nuance in our paper is that migration fear targets immigrants, whereas our Non-White analysts are classified by ethnicity regardless of national origin—many are U.S.-born. Our framework thus requires that migration-related threats activate broader racial out-group biases. This assumption is consistent with research on intergroup threat showing that domain-specific fears can generalize to phenotypically similar out-groups (Stephan and Stephan, 2000; Cottrell and Neuberg, 2005).

2.1 Migration Fear, Trust and Private Information Access

To sharpen our intuition and create empirically testable predictions, we present a simple illustrative example regarding out-group distrust, information access, and forecast error. The goal of the exercise is not to create a fully specified model, but to better ground our empirical conjectures. Additional analytical details can be found in Appendix A.

In our example, an analyst seeks to forecast a firm's quarterly earnings. Two types of information exist: public information (prior earnings, industry trends, macroeconomic data) and private information obtained through direct communication with firm executives. The CEO decides whether to share private information with the analyst based on a trust assessment. We classify analysts as either White or Non-White. Following the social psychology literature on in-group/out-group dynamics (Hamilton (1964);Trivers (1971)), we model trust as dependent upon in-group membership status between the CEO and the analyst. In our setting, out-group dynamics arise mechanically because the overwhelming majority of firms are led by White CEOs. As a result, minority analysts are structurally more likely to interact with executives outside their racial group, independent of individual attitudes or intent.

Societal migration fear thus acts as a friction that reduces trust in out-group members, reducing the likelihood they receive access to private information. For White analysts, the probability of receiving private information is unaffected by migration fears.[5] For Non-White analysts, however, the probability of access declines with increasing societal migration fear. The sensitivity of this decline captures the idea that migration fear does not create distrust from scratch, but rather amplifies latent out-group suspicion that may already exist.

Given this structure, the analyst's forecast depends on their information set. When access is granted, the analyst receives a private signal in addition to public information and can issue a more precise forecast. When access is denied, the analyst must rely solely on public information, resulting in a less accurate forecast. An analyst's realized forecast error therefore falls into one of two states:

- **Low Error State:** The analyst is granted access to private information and forecasts with higher accuracy. The forecast error reflects only the irreducible uncertainty that no party can predict.

- **High Error State:** The analyst is denied access to private information and relies solely on public information. As a result, the analyst's expected forecast error is larger, reflecting both irreducible uncertainty and the private information component that is not revealed to them.

[5]For clarity, the example in Appendix A holds in-group access (λ_W) fixed and lets migration fear reduce out-group access (λ_{NW}). This abstraction does not rule out small changes in White analysts' overall access—for example, if firms expand total Q&A participation in high-attention periods. The empirical predictions require only that Non-White access worsens relative to White access as migration fear rises (i.e., $\partial(\lambda_{NW} - \lambda_W)/\partial\text{Fear} < 0$), allowing λ_W to be flat or modestly increasing.

The analyst's expected forecast error is a weighted average of these two states, where the weights correspond to the probability of being granted or denied access. Because the error without private information is strictly higher than the error with access, any decrease in access probability shifts weight toward the high error state, increasing overall expected forecast error.

The focus of our empirical study is on whether migration fear differentially affects Non-White analysts' forecast accuracy. Because White analysts' access probability is fixed at the baseline level, their expected forecast error is independent of migration fear. In contrast, Non-White analysts' access probability declines as migration fear rises, shifting them from the low error state to the high error state more frequently. This produces a race-based accuracy gap between White and Non-White analysts as migration fear intensifies.

2.2 Predictions

The stylized example from Section 2.1 yields several testable predictions. We organize these into predictions about the main effect, cross-sectional heterogeneity, and analyst forecast behavior.

2.2.1 Main Prediction

When migration fear is low, CEOs share private information relatively evenly across analysts, and Non-White analysts' forecast accuracy is comparable to White analysts'. When migration fear rises, out-group distrust intensifies, reducing the probability of private information access for Non-White analysts. This shifts them more frequently into the high error state, implying that migration fear increases forecast errors for Non-White analysts relative to White analysts. Thus, we expect the magnitude of absolute analyst forecast errors to be positively associated with the interaction of migration fear and Non-White analyst status.

2.2.2 Heterogeneity in Out-Group Bias

Extant research suggests that the sensitivity of out-group bias to society-wide migration fear can vary cross-sectionally across firms. Settings which are more likely to have higher out-group biases against minority immigrants—such as firms with in-group leadership (i.e. White CEOs), Republican-affiliated CEOs (Hajnal and Rivera, 2014; Hainmueller and Hopkins, 2014), or firms headquartered in non-sanctuary areas (Hausman, 2020; Casellas and Wallace, 2020)—should be more impacted by migration fear. In contrast, lower-bias environments—such as firms led by Non-White CEOs, Democratic CEOs, or firms in sanctuary jurisdictions—should exhibit weaker or absent effects. When out-group bias sensitivity is small, even high levels of societal migration fear may produce little differential private access, so the accuracy gap is weak. When sensitivity is large, migration fear substantially reduces Non-White access, and the accuracy gap widens.

2.2.3 The Importance of Firm-Specific News

The framework also suggests that the importance of private information should moderate our main findings. In firms where private information plays a larger role in determining earnings outcomes—those with high idiosyncratic volatility—the high error state is particularly costly. Being denied access when private information matters most amplifies the forecast accuracy gap when Non-White analysts lose access. In firms whose performance tracks macro factors closely (low idiosyncratic volatility), private information matters less, and the impact of migration fear on Non-White analysts' forecast error should be attenuated.

2.2.4 Conference Call Access as Mechanism Validation

A central assumption of our framework is that the increase in Non-White forecast error is driven by a reduction in information access. While it is not possible to empirically observe an executive's private conversations with a given analyst, we can proxy for information access frictions by analyzing disparities in conference call participation. Mayew et al. (2013) and Cohen et al. (2020) find analysts chosen to participate in conference calls have privileged access to information, resulting in better forecasts. Consistent with the prediction that migration fear reduces Non-White analysts' access to private information, we expect Non-White analysts to be less likely to participate in conference calls during periods of high migration fear.

2.2.5 Non-White Analyst Forecast Behavior

Finally, if Non-White analysts recognize their informational disadvantage during high-fear periods, they may adjust their forecasting behavior. Recall that when access is denied, the analyst's forecast collapses to reliance on public information alone. As migration fear rises and access becomes more restricted, Non-White analysts will increasingly discard idiosyncratic private signals and rely more heavily on publicly available information, such as the consensus forecast. This implies greater herding behavior—issuing forecasts closer to consensus, following rather than leading peers, and waiting until just before earnings announcements when more public information is available.

3 Empirical Design

Our empirical tests are designed to capture the impact of migration fear on the forecast accuracy of non-white analysts. Thus, the dependent variable of our investigation is analyst absolute forecast error (*AFE*), where higher levels of error indicate worse accuracy. To assess accuracy, we only calculate *AFE* for the last forecasted EPS prior to the quarterly earnings announcement, and construct the variable in accordance with prior papers (Mikhail et al., 1999; Hong and Kubik, 2003; Merkley et al., 2020):

$$AFE_{i,j,t} = \frac{Abs(ForecastedEPS_{i,j,t} - ActualEPS_{i,t})}{Price_{i,t}} \tag{1}$$

Forecasted EPS is the analysts' quarterly EPS forecast, *Actual EPS* is the EPS announced by the firm in the quarter, and i, j, and t denote firm, analyst, and year-quarter, respectively. The scalar, *Price*, is the firm's stock price at the start of the firm's fiscal year-quarter.[6]

The independent variable which is the main focus of our empirical investigation is the impact of the interaction of migration fear (*MFear*) and indicator variable for ethnic minority analyst, i.e., those classified as *Non-White*, *MFear* $\times$ *Non-White*. *MFear* is the Migration Fear Index as constructed by Baker et al. (2016) standardized to mean = 0 and standard deviation = 1. *Non-White* is an indicator variable that takes a value of one if the analyst's race is classified as Non-White, and zero if White. Section 4 discusses the construction and validation of these variables in

[6] Using a predetermined start-of-quarter deflator avoids simultaneity with within-quarter information events. In robustness, we re-estimate our baseline analyses with percentage mean absolute forecast errors to show that our results are not dependent upon price scaling.

further detail. Eq (2) represents the baseline regression model.

$$AFE_{ijt} = \beta_1 MFear_t \times Non-White_j + \beta_2 MFear_t + \beta_3 Non-White_j + \gamma^{'} \boldsymbol{X} + FE + \varepsilon_{ijt} \quad (2)$$

The regression coefficient for β_1, represents the additional error in Non-White analysts' EPS forecasts for a 1 unit increase in *MFear*. **X** represents a vector of control variables as suggested by prior literature on determinants of forecast accuracy (Clement, 1999; Bradley et al., 2017). **X** includes firm-level characteristics: $Size_{it}$ (logged market cap), $Tobin_{it}$ (Market Value of Assets/Book Value of Assets), and $Number\ of\ Analysts_{it}$ (logged number of analysts issuing forecasts) and analyst-level characteristics: $Female_j$ (indicator for analyst's gender), $Analyst\ Portfolio_{ijt}$ (logged number of firms followed by the analyst in the quarter), $Analyst\ Experience_{ijt}$ (logged number of years in I/B/E/S), $Broker\ Size_{ijt}$ (logged number of analysts at the firms brokerage), and $Horizon_{ijt}$ (logged days prior to the earnings announcement when the forecast was issued).[7] Additional details can be found in Appendix A.

Since our unit of observation for *AFE* is jointly influenced by both firm earnings and analysts' forecasts, our empirical strategy combines vectors of analyst, firm, and time fixed effects, FE, to address potential omitted variable biases. To account for omitted factors affecting firm earnings, such as time-varying macroeconomic uncertainty, we include *Year* fixed effects. Additionally, to capture potential biases or characteristics influencing analyst accuracy (e.g., education, socioeconomic background, proximity to management, firm-specific expertise, or biases), we apply *Analyst, Firm* or *Firm* × *Analyst* fixed effects.

These choices allow us to observe the trade-off between parsimony and granularity and allow us to observe the stability of our coefficients across various specifications. For example, while specifications that include *Year* fixed effects will subsume the majority of unobserved variation used in the analyst-based surprise literature (e.g., So 2013) and *Firm* × *Analyst* will resolve unobservable issues related to the non-random pairing of analysts and firms. However, a high-dimensional fixed effects approach can introduce risks of overfitting and multi-collinearity (Dehaan et al., 2017). Thus, we report results from a wide range of configurations with regression diagnostics when we discuss

[7] Analyst Portfolio, Analyst Experience and Broker Size vary at the analyst-quarter level (jt) and then are attached to each forecast (i)

our results in Section 5 and allow the data to speak as to which model appears most optimal for the remainder of our analyses.

Additionally, we report results using a fully interacted version of the baseline model with *MFear*.

$$\begin{aligned} AFE_{ijt} = &\beta_1 MFear_t \times Non\text{-}White_j + \beta_2 MFear_t + \beta_3 Non\text{-}White_j \\ &+ \gamma' \boldsymbol{X} + \delta' MFear_t \times \boldsymbol{X} + FE + \varepsilon_{ijt} \end{aligned} \tag{3}$$

In the fully interacted model, *MFear* is interacted with all other covariates in **X**, allowing us to assess whether the impact of *MFear* on *AFE* is unique to the interaction with *Non-White* status. For example, if the other interactions (e.g., *MFear* × *Female*, *MFear* × *Size*, *MFear* × *Tobin*) are insignificant while *MFear* × *Non-White* is significant, the fully interacted model functions as a falsification test. This strengthens the argument that *MFear* specifically impacts Non-White analysts, ruling out alternative explanations like *MFear* capturing general forms of discrimination (which might also affect female analysts), heightened macroeconomic uncertainty (which could disproportionately affect smaller or more distressed firms), or overall levels of distraction or stress (which could impair analysts' information processing capabilities). For all regressions, we report t-statistics based on two-way clustered standard errors by analyst and by quarter. Clustering by quarter accounts for shocks common to all analysts and firms within a given period, consistent with the quarter-level variation in migration fear. Clustering by analyst allows for correlation in forecast errors for a given analyst across firms and over time. This two-way clustering structure aligns with the level of variation in the main explanatory variables and provides a conservative correction for cross-sectional and temporal dependence.

4 Sample Construction and Descriptive Statistics

4.1 Identifying Non-White Analysts

Our sample consists of US sell-side analysts and the firms they cover in the merged CRSP-COMPUSTAT data set from January 1990 through December 2023. We obtain the full name and brokerage house affiliation of sell-side analysts responsible for the EPS forecasts using the I/B/E/S detailed history recommendation database and Thomson Reuters Investext. Using the analyst's first and last name, we use NamePrism API service to classify each analyst's ethnicity into one of the following groups, based on the group with the highest predicted probability: White, Black, Asian, and Hispanic and label all Non-White analysts with an indicator variable, Non-White.[8]

Among all 3,629 analysts identified above, our Non-White analysts sample includes 462 analysts (12.73%), among which 389 analysts (10.72%) are Asian, 46 analysts (1.27%) are Hispanic, and 27 analysts (0.74%) are Black. Consistent with the sample composition of Kumar, Rantala, and Xu (2021), our data suggest Asians are the predominant minority group among financial analysts, followed by Hispanics and Blacks.

4.2 Measure of Migration Fear

Our measure of Migration Fear is a standardized version of the Migration Fears Index developed by Baker et al. (2016). This index quantitatively assesses societal concerns related to migration by analyzing the proportion of newspaper articles containing specific terms associated with migration and fear, relative to the total number of articles published in a given calendar quarter. The migration-related terms used in the index include "immigration, migration, assimilation, migrant, immigrant, asylum, refugee, open borders, border control, Schengen, and human trafficking." Terms related to fear encompass "anxiety, panic, bomb, fear, crime, terror, worry, concern, and violent." By tracking the presence of these terms in newspaper articles, the index offers insights into the extent to which migration issues are discussed alongside fear during a particular period.

The Migration Fears Index has been previously validated in academic research. Baker et al. (2016) found that the index peaked in European countries during 2015, coinciding with the refugee crisis from the Middle East and North Africa, highlighting the index's capability to track migration concerns. Figure 1 presents a time-series overview of the US Migration Fear Index, showing significant fluctuations over time, with peaks occurring around notable events associated with heightened

[8]NamePrism is a nationality/ethnicity classification tool trained on a 74 million labeled name set from 118 countries, the system links name embeddings for name parts (first/last names) and classify names to 39 leaf nationalities and 6 U.S. ethnicities, including White, Black, API (Asian and Pacific Islander), AIAN (American Indian and Alaska Native), 2PRACE (more than 2 race) and Hispanic. Until June 2019, the system has been used in more than 200 social science and economic research projects, with many published in top economics and finance journals (for example, Diamond et al. (2019); Gornall and Strebulaev (2020); Griffin et al. (2021)).

societal concerns about migration, such as the 9/11 terrorist attacks and Trump's early immigration policy initiatives.

4.3 Descriptive Statistics and Univariate Results

We obtain the last quarterly forecast for each reporting analyst-firm-quarter in the I/B/E/S detail file prior to the earnings announcement and merge this observation with the relevant regression variables using data from I/B/E/S, COMPUSTAT and CRSP. We winsorize observations at 1%. Our final merged regression sample consists of 1,360,603 quarterly EPS forecasts and 132,257 analyst-year-quarter observations for 3,629 unique analysts.

Table 1 presents the descriptive statistics for the variables used in the main regression analyses. Among the full sample of analyst quarterly forecasts included in the sample, Non-White analysts issued 11.9% of all quarterly EPS forecasts; the median forecast error is about 0.2% of the firm's stock price. An average analyst follows 12.7 firms and is affiliated with brokerage houses that employ 17.9 analysts. The sample forecasts on average are issued 40 days ahead of the fiscal quarter end, and firms in the sample have an average of 5.8 analysts following them. Consistent with prior literature (Kumar, 2010; Peng et al., 2022), we find female analysts account for about 9.2% of all quarterly forecasts.

Figure 2 plots the association between *AFE* and deciles ranks of migration fear for Non-White analysts and for white analysts, with 95% confidence intervals. While there is no obvious relation between migration fear decile and overall analyst forecast accuracy, the figure illustrates an accuracy GAP, i.e. the white space in between the orange line (*Non-White AFE*) and and turquoise line (*White AFE*) that becomes wider with higher deciles of migration fear. Figures 3 and 4 confirm this univariate association between Migration fear and the accuracy gap. In Figure 3, we plot Mean *AFE* for both *White* and *Non-White* analysts by year-quarter on the Y-axis, and *MFear* on the X-axis, and plot the best fit line for each group. The slope for *Non-White* (0.0003) vs. *White* (-0.0003) suggests that forecast accuracy appears to get worse for *Non-White* analysts, while it appears to improve for *White* analysts. At a univariate level, these results would be consistent with prior papers Fershtman and Gneezy (2001); Iyengar and Westwood (2015) that show both in-group favoritism and out-group discrimination when the in-group feels threatened. Figure 4 plots the accuracy gap as *Non-White AFE* minus *White AFE* for each year against *MFear* and shows that relative analyst accuracy gets worse for *Non-White* with increasing levels of *MFear* (*slope = 0.0007*, $\rho = 0.24$). Collectively, our univariate figures suggest that migration fear has a negative impact on Non-White analyst forecast accuracy, relative to that of White analysts.

5 Main Findings: Migration Fear and Analyst Forecast Error

Table 2 tabulates regression results from Eq (2) and Eq (3) across various dimensions of fixed effects. From left to right, we increase the granularity of the fixed effects configuration from the most parsimonious to the most granular. Several findings emerge with regard to our variable of interest. First, the coefficient on *MFear* $\times$ *Non-White* is positively and significantly associated with AFE, and this relation is robust across a variety of fixed effect vectors and interactions, with $p < 0.01$ across all 8 columns. Second, we observe very little variation in the coefficient on *MFear* $\times$ *Non-White* across specifications. The coefficient has a high value of 0.00062 ($t = 3.56$) in Column (2), which uses Year, Firm and Analyst fixed effects, and a low of 0.00055 ($t = 3.28$) in Column (8), the most specified configuration that controls for *Year* and *Firm* $\times$ *Analyst* fixed effects while also interacting *MFear* with all controls. The stability of the coefficient indicates that multicollinearity is not distorting the coefficient estimate and that the model is well-specified, with minimal confounding among covariates. Third, the impact of migration fear on Non-White analyst forecast accuracy is economically meaningful. Using the most stringent models in our sample, i.e. Columns (8) and the average share price of \$72.10 (untabulated), a one standard deviation increase in *MFear* results in an increase in absolute forecast error for a Non-White analyst of approximately 4 cents per share in terms of EPS ($\$0.04 = \$72.10 \times 0.00055$), an increase of roughly 8%.

Two additional findings related to *MFear* merit discussion. The main effect of *MFear* is insignificant across all models. Because this variable measures the impact of migration fear on *White* analyst forecast accuracy, these findings collectively show that migration fear only has a negative impact on the forecast accuracy of Non-White analysts when controls are included, as opposed to the negative slope in Figure 3 which suggested increased accuracy (lower AFE) for *White* analysts when migration fear is increased. Additionally, in Columns (5) - (8) where we report the fully interacted model results, the coefficient is insignificantly different from zero in 27 of 32 interactions across all four specifications.[9] Overall, the fully interacted models indicate that migration fear operates through a narrow and specific margin rather than proxying for a broad set of omitted factors. The MFear × Non-White interaction is robust and stable across specifications, while the remaining interactions are unstable and lack a coherent pattern. This contrast suggests that the effects of migration fear are concentrated along a particular dimension, rather than reflecting more diffuse forces that impair forecast accuracy across analysts.

This collective lack of significance is important, as it strengthens the argument that *MFear* is a well-specified measure of migration fear and is unlikely to also capture potential correlated omitted variables such as macroeconomic uncertainty or societal gender discrimination that could influence analyst forecast errors.

Finally, we perform regression diagnostics to evaluate whether our most detailed models— incorporating 103,591 fixed effects across 1,336,210 observations—may be affected by multicollinearity. DeHaan (2020) warns that model overspecification can create a misleading impression of the useful variation available for estimating the coefficient of interest, despite a large number of observations. To address this, we follow Armstrong, Kepler, Samuels, and Taylor (2022) and report the variance inflation factor (*VIF*) and the *% of Variation Absorbed by Fixed Effects* for the interaction term *MFear × Non-White*. In Column (8), the most specified models yield VIF values of 1.681 , indicating that adding high-dimensional fixed effects does not introduce problematic multicollinearity, as the VIF remains well below the standard threshold (Belsley, Kuh and Welsch, 1980). Additionally, the *% Variation Absorbed by Fixed Effects* is relatively low (19.5%), suggesting that *MFear × Non-White* retains adequate variability for meaningful interpretation. Between Columns (4) and (8), the adjusted R^2 is identical; thus, we proceed with the more parsimonious model, excluding the fully interacted version from further analyses. Given that our model in subsequent analyses include both *Year* and *Firm × Analyst* fixed effects and that our dependent variable, *AFE*, is measured at

[9] A small number of MFear $\times X$ interactions attain statistical significance in isolated specifications, most notably interactions with Size, Analyst Experience, and the number of analysts following the firm. These effects are neither stable across fixed-effect configurations nor consistent in sign or magnitude across columns. Moreover, their economic magnitudes are small relative to the MFear × Non-White coefficient, and they do not form a coherent pattern pointing to a specific alternative mechanism, such as generalized macroeconomic uncertainty or broad-based discrimination unrelated to analyst race.

the *Firm* $\times$ *Analyst* $\times$ *Year-Quarter* level, our empirical model effectively controls for all year and firm-analyst specific factors, leaving only quarterly variation (such as the impact of migration fear on Non-White analysts) to explain changes in *Absolute Forecast Error (AFE)*. This model allows us to hone directly on the primary dynamics of interest while mitigating the risk of overfitting.

6 Identification

To further strengthen our identification, we examine a setting that generates plausibly exogenous shifts in the migration-related information environment: the 2016 U.S. presidential election.[10] During this period, immigration and border policy became unusually salient in public discourse, coinciding with sharp increases in media coverage and public attention to migration-related issues. Crucially, the timing of this event is externally determined and orthogonal to analyst-specific, time-varying characteristics such as brokerage resources, coverage intensity, or portfolio composition. As a result, this setting helps isolate variation in migration fear arising from broad societal and informational shifts, rather than from endogenous changes in analysts' work environments or information-processing constraints.

6.1 Donald Trump's 2016 Presidential Election Campaign

Donald Trump announced his candidacy for the U.S. presidency on June 16, 2015. Immigration enforcement and refugee policy quickly became central themes of his campaign. Public statements and campaign messaging emphasized stricter enforcement of existing immigration laws, increased deportations of undocumented immigrants, and restrictions on refugee admissions. These messages frequently framed immigration in terms of crime, terrorism, and national security risks, including claims linking refugee inflows following the November 2015 Paris attacks to heightened public safety concerns(Helbling and Meierrieks, 2022). Related rhetoric also echoed narratives advanced by European nationalist parties regarding the social and cultural consequences of large-scale migration.

[10]While the 2016 election coincided with broader political and macroeconomic developments, our identification leverages variation in migration-related discourse that is orthogonal to standard macroeconomic indicators and analyst-specific conditions. In Section 8, we show that our results are robust to controlling for contemporaneous measures of economic uncertainty, mitigating concerns that our findings reflect confounding macroeconomic shocks rather than shifts in the migration-fear environment.

Contemporary media coverage and public discourse characterized this period as one of heightened nationalist and exclusionary sentiment, coinciding with a marked increase in migration-related fear. Consistent with this interpretation, Figure 1 shows that the *MFear* index begins to rise in late 2015 following the launch of Trump's campaign, peaks during the first year of his presidency, and remains elevated thereafter. Rupar et al. (2024) document parallel shifts in racial sentiment, including a sharp increase in Google searches for "White Nationalism" following the election, with elevated levels persisting throughout Trump's presidency. Taken together, these patterns indicate a broad-based increase in migration fear rather than sentiment confined to a particular immigrant group.

We exploit the onset of Trump's presidential campaign as a discrete shift in societal attitudes toward immigration and use it to estimate the effect of migration fear on analyst forecast accuracy in a difference-in-differences design. Specifically, we construct an indicator variable, *PostCampaign*, equal to one for forecasts issued during 2016–2019 and zero for forecasts issued during 2011–2014. The analysis spans 32 quarters—16 before and 16 after the campaign—and includes *Firm* × *Analyst* fixed effects to absorb time-invariant features of analyst–firm relationships. To reduce contamination from transitional changes in sentiment during the campaign's launch year, we exclude forecasts issued in 2015. This approach yields a clean comparison between pre-campaign and post-campaign periods and allows *PostCampaign* to capture the common shift in forecast accuracy associated with the campaign-induced change in migration attitudes.

$$AFE_{ijt} = \beta_1 \text{PostCampaign}_t + \beta_2 \big(\text{PostCampaign}_t \times \text{Non-White}_i\big) + \gamma' X_{ijt} + FE_{\text{Firm}\times\text{Analyst}} + \varepsilon_{ijt}. \tag{4}$$

The Non-White main effect is absorbed by the Firm × Analyst fixed effects. The coefficient of interest, β_2, captures the differential change in forecast accuracy for Non-White analysts in the post-campaign period. Table 3 presents the results. The coefficient on *PostCampaign* × *Non-White* is positive and significant *(coeff = 0.00344, t = 4.81)*, corroborating our main findings that increased migration fear significantly impairs the forecast accuracy of Non-White analysts.[11] Figure 5 further supports our identification strategy by demonstrating that the design satisfies the

[11] Main effects of *Non-White* are subsumed by *Firm x Analyst* fixed effects.

parallel trends assumption. Year-by-year estimates of the Event *Year × Non-White* coefficient indicate no significant effects in the years prior to the campaign (2011-2014), then become positive although insignificant in the first year after the campaign (2016) and remain positive and significant in the inauguration year (2017) and throughout the first three years of the term (2018-2019). Notably, the magnitude of *AFE* is significantly larger in the *PostCampaign* era, 5.7 times larger than our baseline findings in Table 2 (*0.00344 vs 0.0006*). Several explanations may account for this economic magnitude. First, the Trump campaign may represent a discrete regime shift in the salience and social acceptability of migration-related biases, rather than a continuous movement along the MFear distribution—the campaign did not merely increase fear but fundamentally changed the public discourse around immigration. Second, the DiD estimate captures the cumulative effect of sustained elevated migration fear over multiple years, whereas the baseline coefficient reflects the marginal impact of quarter-to-quarter variation in MFear. Third, measurement error in the news-based MFear index likely attenuates baseline estimates toward zero; the binary PostCampaign indicator, by contrast, is measured without error, potentially yielding estimates closer to the true effect. Overall, these results reinforce the idea that heightened migration fear following Trump's campaign and election disproportionately harmed the forecast accuracy of *Non-White* analysts.

7 Mechanism and Cross-Sectional Evidence

Section 5 documents the negative association between migration fear and Non-White analyst forecast accuracy, while Section 6 strengthens our causal inferences through a quasi-exogenous setting. In this section, we test the conjectures developed in Subsections 2.2.2 through 2.2.4 by examining cross-sectional variation in the migration-fear penalty across settings that differ in the strength of out-group distrust and access to firm-specific information. We split the sample based on the factors that we expect to capture the heterogeneity of migration fear on minority analysts' information access and compare the coefficients on *MFear × Non-White* from Eq (2) across these subsamples.

7.1 Cross-Sectional Heterogeneity

As discussed in Section 2.2, trust is a crucial factor in effective communication and prior research indicates that in-group biases can increase CEOs' willingness to share private information while out-group biases may amplify distrust and hinder information flows. In our setting, the impact of trust is of paramount importance, as CEOs face potential legal consequences for tipping analysts with private information. Thus, we test whether migration fear reduces Non-White analysts' forecast accuracy when out-group distrust is strongest, as the firms become less likely to share private information with minority analysts, thus increasing the probability their forecasts end up in the high error state. We examine three cross-sectional cuts of the panel: the first is based upon CEO ethnicity, where out-group bias is reduced if both the CEO and analyst are Non-White, the second is based on whether the firm is headquartered in pro-immigrant Sanctuary areas, where out-group bias is assumed to be lower, and the last is based on the CEO's political affiliation, where out-group bias is assumed to be lower if the CEO is a Democrat.

7.1.1 CEO Ethnicity and Migration Fear

We obtain CEO ethnicities using classifications by Rupar et al. (2024) based on hand-collected photos for a sample of S&P 1500 firms from 2005-2019. We then partition into two subsamples, depending on whether the CEO is *White* or *Non-White*, allowing us to directly test for out-group bias. We obtain a sample of 27,336 (595,066) observations for those with Non-White (White) CEOs. Table 4, Columns 1 and 2 re-tabulate our baseline regression across subsamples. We find that *MFear* $\times$ *Non-White* is positive and significant when the CEO is *White* (*coeff = 0.0005, t = 3.16*), but negative and insignificant when the CEO is *Non-White* (*coeff = -0.00006, t = -0.31*). That is, our results are consistent with the notion that information flows to Non-White analysts are only reduced when the CEO is White.

The difference in coefficients across CEO-ethnicity subsamples (p-value = 0.02) is more consistent with explanations based on differences in information access relative to a general distraction or bandwidth effect which would be expected to affect Non-White analysts similarly regardless of CEO ethnicity. Instead, the Migration Fear penalty we document is strongly pronounced under White CEOs and insignificant under Non-White CEOs, suggesting the importance of context and out-group interactions. While this evidence alone does not uniquely identify the underlying channel, it is difficult to reconcile with broader processing impairment stories and instead points to frictions that vary with the analyst–firm relationship.

7.1.2 Sanctuary Areas and Migration Fear

Sanctuary areas are jurisdictions that have policies limiting cooperation with federal immigration enforcement to prioritize community trust in local law enforcement. These policies aim to protect undocumented immigrants from deportation, fostering an environment that emphasizes inclusivity and support. We posit that firms headquartered in these sanctuary areas may reflect "pro-immigrant" values and be less influenced by migration fear. Therefore, we expect our baseline results to be more pronounced in the Non-Sanctuary subsample, where heightened immigration concerns are more likely to contribute to trust barriers between firms and minority analysts. Data on immigration policies are sourced from the Center for Immigration Studies, a non-profit research organization founded in 1985.[12]

In Table 4, Column 3 and 4, we report baseline regression findings where we partition the sample based on whether the firm resides in Sanctuary and Non-Sanctuary counties. Results show that the impact of *MFear* on Non-White analyst accuracy vanishes for Sanctuary headquartered firms (*coeff = 0.00005, t = 0.65*) and is positive and significant in Non-Sanctuary counties (*coeff = 0.00022, t = 3.13*). The difference in these coefficients is statistically significant (*p-value = 0.07*) and corroborates those in 7.1.1, that migration fear and distrust may impede the flow of private information from the firm to the analyst, ultimately affecting the accuracy of their forecasts.

7.1.3 CEO Political Affiliation and Migration Fear

Because political preferences are strongly correlated with views on immigration, diversity, and regulation (Hajnal and Rivera, 2014; Hainmueller and Hopkins, 2014), the firm's partisan leadership is likely to shape how migration fear translates into attitudes and trust toward minority outsiders.[13] In Table 4, Column 5 and 6, the CEO Partisan panel shows that this negative impact on forecast

[12] `https://cis.org/Map-Sanctuary-Cities-Counties-and-States`

[13] CEO political affiliation is inferred from personal campaign contributions to Democratic and Republican recipients, shared by Arikan et al. (2023). We thank the authors of the paper for sharing their data.

accuracy is not uniform across firms, but is significantly stronger when the firm is led by a Republican CEO. When we split the sample by CEO political affiliation, the interaction between minority status and migration fear remains positive and significant in both groups, but is substantially larger for firms with Republican CEOs (*coeff = 0.00087, t = 4.93*) than for those with Democratic CEOs (*coeff = 0.00038, t = 2.43*). A formal test rejects equality of these coefficients (*F-test, p = 0.029*), indicating that heightened migration fear erodes Non-White analysts' forecast accuracy more in Republican-led firms. These patterns are consistent with our mechanism: migration fear amplifies out-group distrust in politically less immigrant-friendly environments, leading to larger informational disadvantages for minority analysts and more severe performance penalties in those settings.

7.2 Private Information Access and Migration Fear Penalty

To more directly probe the mechanism underlying the migration-fear penalty, we examine whether its magnitude varies systematically with analysts' access to private, firm-specific information. Our framework yields two complementary predictions. First, the penalty should be more pronounced in settings where private information plays a larger role in price formation. Second, heightened migration fear should manifest in observable differences in access to discretionary information channels, such as conference-call Q&A sessions, with the penalty largest when such access is limited. We evaluate these predictions in turn.

7.2.1 Importance of Private Information

We operationalize the importance of private information using firm-level idiosyncratic volatility. Specifically, we split the sample at the median level of idiosyncratic volatility, computed from residuals of a four-factor Fama–French asset pricing model. Higher idiosyncratic volatility reflects greater reliance on firm-specific information in price formation, whereas lower idiosyncratic volatility indicates outcomes that are more closely tied to common market and macroeconomic factors (Ang et al., 2006; Harford et al., 2019).

Table 5A reports the results. Consistent with the mechanism outlined above, the coefficient on *MFear* $\times$ *Non-White* is significantly positive in the high–private-information subsample (*coeff*

= 0.00075, t = 3.24) but is economically small and statistically insignificant in the low–private-information subsample (*coeff* = 0.00009, t = 1.47). The difference across subsamples is statistically significant ($p < 0.01$), indicating that the migration-fear penalty is concentrated in settings where private information plays a more central role in valuation.

7.2.2 Migration Fear and Information Access Frictions: Evidence from Conference Calls

We test conference-call as a channel of information access by examining whether migration fear is associated with differential participation in earnings-call Q&A sessions and whether this access margin is linked to the magnitude of the migration-fear accuracy penalty. Conference-call Q&A represents a discretionary and interactive disclosure channel through which analysts can obtain firm-specific information, making it a natural setting in which selective access to management is empirically observable.[14]

Table 5B examines whether migration fear affects analysts' likelihood of participating in the Q&A portion of earnings calls. We estimate logistic regressions in which the dependent variable equals one if the analyst participates in the Q&A session. Column (1) shows that the interaction between migration fear and minority status is negative and highly significant (*MFear* × *Non-White*: *coeff* = −0.057, $z = -5.79$), indicating that heightened migration fear is associated with reduced Q&A access for Non-White analysts. Consistent with baseline disparities documented in prior work, Non-White analysts are also less likely to participate on average (*Non-White* = −0.110, $z = -10.46$).

At the same time, the main effect of migration fear is positive (*MFear* = 0.0077, $z = 2.03$), suggesting that firms modestly expand overall Q&A activity during high-fear periods. Taken together, these estimates point to a pattern of selective access: while interactive disclosure becomes more prevalent on average, incremental access is disproportionately allocated away from Non-White analysts. Economically, a one–standard deviation increase in migration fear reduces the probability that a Non-White analyst participates in the Q&A by approximately 5.7 percentage points relative

[14]Because we do not observe analysts' attempts to ask questions or firms' call-management decisions, we interpret conference call participation as reflecting *net information access frictions* between the analyst and the firm, rather than intentional exclusion or reduced analyst demand.

to White peers.[15]

Table 5C links this access margin to forecast performance by examining whether the migration-fear accuracy penalty varies with conference-call participation. Because participation reflects both migration fear and analyst–firm interactions, it provides a natural dimension along which informational frictions should differentially affect forecast accuracy if selective access is operative.

Guided by this logic, we split the sample into forecasts associated with calls in which the analyst participated (*CC Participated*$= 1$) versus did not participate (*CC Participated*$= 0$) and estimate OLS regressions of absolute forecast error (AFE) within each subsample. The interaction *MFear* $\times$ *Non-White* is positive and statistically significant in both subsamples, but its magnitude is nearly three times larger when the analyst does not participate in the Q&A session (*coeff* $= 0.00091$, $t = 3.99$) than when the analyst participates (*coeff* $= 0.00033$, $t = 2.21$). The difference in magnitudes is statistically significant (*F-test,* $p = 0.061$) and economically meaningful.

This split-sample analysis is not intended to identify a causal treatment effect of conference-call participation. Rather, it points to evidence of increased frictions in real-time, trust-based communication channels: the migration-fear penalty for Non-White analysts is amplified precisely when a salient interactive information channel is unavailable. Using the average share price in our sample, a one–standard deviation increase in migration fear corresponds to an incremental forecast error of approximately 6–7 cents per share when Non-White analysts do not participate in the call, compared to approximately 2–3 cents when they do.

Although the penalty is attenuated among participating analysts, it does not disappear. This pattern suggests that conference-call participation is a noisy proxy for broader access to firm-specific information rather than a binary switch that fully equalizes information environments. Even among participants, analysts may differ in the quality and depth of information received—for example, through question sequencing, follow-up opportunities, or private post-call interactions (Brown et al., 2015). Additional information frictions may also operate through other communication channels.

[15] *Analyst* $\times$ *Firm* fixed effects are omitted from the logistic specification because identification in nonlinear fixed-effects models relies on within-pair variation in participation. Given the high persistence of conference-call participation within analyst–firm pairs, such a specification would eliminate a substantial fraction of observations and raise identification concerns (Neyman and Scott, 1948; Lancaster, 2000).

7.3 Strategic Adaptation: Evidence from Forecasting Behavior

The evidence thus far indicates that migration fear is associated with reduced access to private, firm-specific information for Non-White analysts. A natural question is how analysts respond to this disadvantage. One possibility is that disadvantaged analysts recognize constraints on their access to private information and strategically adapt by placing greater weight on publicly observable signals, including peer forecasts that may incorporate more advantaged sources of information.

We study this possibility by examining whether migration fear is associated with increased herd-like forecasting behavior among Non-White analysts. Importantly, herding is an effortful and deliberate forecasting strategy: it requires analysts to track peer forecasts, assess the evolving consensus, and strategically position their own forecasts relative to it. As such, herding reflects active information processing and intentional substitution toward public information rather than disengagement.

Table 6 reports results for three complementary measures of herding behavior. The first outcome is a herding indicator, *Herding*, following Gleason and Lee (2003), which identifies forecast revisions that move toward the consensus forecast. Column (1) shows that a one-standard-deviation increase in migration fear increases the probability that a Non-White analyst issues a herding forecast by approximately 2.0% (t = 3.42). The second outcome, *Last Minute Forecast*, captures forecasts issued in the final 1–6 calendar days prior to the earnings announcement (Xing, 2015). Column (2) shows that heightened migration fear increases the likelihood that Non-White analysts delay forecast issuance until shortly before the announcement ($t = 2.20$), precisely when public information is most abundant. This timing response is consistent with deliberate information substitution toward public signals. The third outcome is the *Lead–Follow Ratio* (LFR) from Shroff et al. (2014), which captures whether an analyst tends to issue forecasts earlier or later than peers covering the same firm. Column (3) indicates that higher migration fear significantly increases the likelihood that Non-White analysts' forecasts are classified as follower forecasts ($t = -6.98$). This pattern reflects strategic positioning—waiting to observe peers' forecasts before committing—rather than reduced engagement with the forecasting task.

Taken together, features of these these results support a strategic-adaptation of Non-White forecasting behavior when faced with the loss of private information during high migration fear periods. The timing and positioning patterns—following rather than leading, allowing the consensus to most fully form information, then revising toward consensus—are internally coherent and indicative of purposeful information-gathering behavior. Third, taken together with the conference-call participation results, the evidence points to selective information access: when interactive channels are constrained, disadvantaged analysts substitute toward publicly available information rather than disengaging.

A natural question is why increased herding does not fully offset the accuracy penalty documented in our main tests. If Non-White analysts converged entirely to the consensus, their forecast errors would equal the consensus error—likely lower than what we observe. The persistence of elevated forecast error despite increased herding suggests that analysts stop short of full convergence, consistent with career concerns that penalize the appearance of possessing zero private information (Hong and Kubik, 2003). This leaves affected analysts in an intermediate position: stripped of the private access that previously allowed them to outperform, yet unable to fully embrace consensus without signaling their informational disadvantage. The result is a "second-best" forecasting strategy that reduces but does not eliminate the accuracy penalty.

Overall, these findings suggest that migration fear induces a strategic reallocation of information sources among Non-White analysts. Their forecasting behavior indicates strategic adjustment for constrained access to private information, reinforcing our theory of reduced information-access. Notably, such behavior is difficult to reconcile with an alternative explanation in which migration fear impairs Non-White analysts' information-processing capacity. Cognitively impaired analysts would likely be unable to engage in such systematic, purposeful adaptation. We confirm this by ruling out resource constraints in Section 8.

8 Robustness

In Section 8 we aim to provide comfort that our findings are not driven by alternative explanations and are not driven by particular design choices. We begin by first examining the possibility that Non-White analysts' reduced accuracy could also be driven by reduced cognitive abilities (e.g. limited bandwidth; pessimism) that are moderated by migration fear. Next, we re-examine our main finding across a number of alternate specifications to provide assurance that our results are not driven by a particular choice of *AFE* or *MFear*, while also performing additional tests to address non-random matching of analysts to firms. Finally, we rule out the idea that migration fear maybe correlated with macroeconomic uncertainty–and that Non-White analysts may be inferior at processing such information.

8.1 Migration Fear and Non-White Analysts' Limited Bandwidth

We begin by exploring the possibility that Non-White analysts' information processing capacity (DeHaan et al., 2015; Drake et al., 2020) may be further constrained during periods of heightened migration fear, potentially due to distraction or reduced cognitive bandwidth (Hirshleifer and Teoh, 2003; Pan et al., 2024). If such limitations contribute to the decline in forecast accuracy among Non-White analysts, the effect should be most pronounced for analysts who are already relatively resource constrained.

In Table 7A, we test this implication by splitting the sample using two established proxies for analyst resources: median *Brokerage Size* and the median number of firms covered in an analyst's portfolio (Clement, 1999; Hong and Kubik, 2003; Kadan et al., 2012). Under a limited-bandwidth explanation, Non-White analysts at smaller brokerages or with larger portfolios should be more adversely affected by migration fear. Across both splits, however, the equality tests fail to reject the null that the *MFear* $\times$ *Non-White* coefficients are equal (*# of Companies*: $p = 0.8739$; *Brokerage Size*: $p = 0.6553$). While these results do not rule out bandwidth constraints as a contributing factor, they provide little evidence that generalized limitations in analysts' processing capacity are a primary driver of the migration-fear penalty we document.

8.2 Migration Fear and Non-White Analysts' Pessimism

We next consider whether heightened migration fear induces a directional bias in Non-White analysts' forecasts, such as excessive pessimism, which could mechanically increase forecast errors. To examine this possibility, we replace absolute forecast errors with signed forecast errors, defined as forecasted EPS minus realized EPS, and re-estimate the baseline specification.

As reported in Table 7B, the coefficient on *MFear* $\times$ *Non-White* is small and statistically insignificant (*coeff* = 0.00002, t = 0.26), indicating no evidence of a systematic directional bias associated with migration fear. These results suggest that the documented increase in forecast errors does not reflect pessimistic forecasting behavior among Non-White analysts during high-fear periods.

Taken together, these analyses of alternative mechanisms, along with the cross-sectional evidence based on CEO ethnicity and sanctuary jurisdiction status and the conference-call participation results, help narrow the set of plausible explanations for the migration-fear penalty. While no single test is determinative, the combined evidence is difficult to reconcile with explanations based on generalized processing constraints or directional forecasting bias. Instead, among the mechanisms considered, the conference-call evidence documented in Tables 5A and 5B provides the most direct support for an information-access interpretation: the migration-fear penalty is concentrated in settings where analysts are excluded from interactive firm disclosures and is meaningfully attenuated when that channel is available.

8.3 Analyst Forecast Error scaled by Mean Absolute Forecast Error

To provide comfort that our results are not driven by the choice of scaling variable in *AFE*, we calculate a percentage mean absolute forecast error (*PMAFE*), following Clement (1999). We scale each analyst's forecast error by the mean absolute error in each year-quarter. Using *PMAFE* in our baseline regression provides consistent results: Table 8, Column 1, shows that the coefficient on *MFear* × *Non-White* is 0.0115 (t = *3.30*), demonstrating that the effect of migration fear on forecast accuracy is robust to different scaling methods.

8.4 Entropy Balanced Covariate Samples

While our use of firm-analyst fixed effects removes the influence of potential confounds that stem from non-random assignment of analysts to firms, we nonetheless check the robustness of our results to an entropy balanced-covariate sample across *White* and *Non-White* analysts. We weight observations to match the mean and variance of all of our covariates and re-estimate our Eq (2). Table 8 Column 2 tabulates findings and shows that *MFear* × *Non-White* remains positive and significant (*coeff =0.00054, t = 3.22*) and virtually unchanged from Table 2 Column 8 (*coeff* =

0.00055, t = 3.28) suggesting that covariate imbalance is unlikely to drive the results of our findings.

8.5 Migration Fear as measured by Gallup's Poll on Immigration Policy

To address concerns that our results may be specific to our measure of *MFear*, we examine our baseline findings with an alternate measure of migration fear. We create a variable, *MFear Gallup*, which is a survey asked by Gallup to Americans about their preferred immigration levels. Gallup's polls on immigration typically measure public opinion in the United States regarding various aspects of immigration policy, including attitudes towards immigrants, border security, and potential reforms. While our primary measure of migration fear captures societal perceptions of immigrants as reflected in media articles, our alternate measure captures migration fear as directly measured from survey respondents. Table 8 Column 3 shows the impact of *MFear Gallup* $\times$ *Non-White* to be positive and significant with the significant economic impact (*coeff = 0.00036, t = 3.11*) while the coefficient remains statistically significant ($p < 0.01$). This indicates that *MFear* is not simply capturing media bias and that the impact of xenophobia is robust to alternative measures based on well-known and reputable survey data.

8.6 Residualized Migration Fear to Macroeconomic and Trade Uncertainty

To assuage concerns that *MFear* may be correlated with broader macroeconomic or trade policy uncertainty–and that Non-White analysts may be differentially affected by such uncertainty—we residualize *MFear* to isolate variation orthogonal to these factors. Specifically, we first regress *MFear* on a vector of macroeconomic variables measured at the year–quarter level, including the implied volatility of the S&P 500 (*VIX*), a newspaper-based measure of Economic Policy Uncertainty (*EPU*) from Baker et al. (2016), gross domestic product growth, the unemployment rate, and net migration into the United States. Using the fitted values from this regression, we construct $MFear^{\perp}$ as the residual component of *MFear* that is orthogonal to these macroeconomic conditions. We then replace *MFear* in our baseline specification with $MFear^{\perp}$.

If the estimated coefficient on the interaction *MFear* $\times$ *Non-White* were driven by correlated macroeconomic uncertainty rather than migration-related sentiment, we would expect this interaction to attenuate once such variation is removed. The results, reported in Table 8 Column (4), show that the interaction remains positive and statistically significant (*coeff* $= 0.00966$, $t = 3.65$), indicating that our main findings are unlikely to be explained by omitted macroeconomic factors.[16]

In Column (5), we further residualize *MFear* with respect to trade policy uncertainty using the U.S. and China Trade Policy Uncertainty indices from Baker et al. (2016). This specification addresses the possibility that Non-White analysts may be more likely to cover firms with exposure to international supply chains or foreign stakeholders, for which elevated trade policy uncertainty—rather than migration-related sentiment—could independently increase forecast difficulty. The interaction *MFear* × *Non-White* remains positive and statistically significant in this specification (*coeff* $= 0.00956$, $t = 3.62$), further supporting the interpretation that our results are not driven by correlated trade-related uncertainty.

9 Conclusion

We document that societal migration fear is associated with economically meaningful disparities in the forecast accuracy of Non-White financial analysts. A one-standard-deviation increase in migration fear corresponds to approximately four cents per share, or an 8% increase, in absolute forecast error for the average Non-White analyst. To mitigate endogeneity concerns, we employ a rich fixed-effects structure that accounts for non-random analyst–firm matching and common sources of aggregate uncertainty. We further show that forecast accuracy for Non-White analysts deteriorates following the sharp rise in migration-related rhetoric surrounding the 2015–2016 U.S. presidential election, consistent with heightened migration fear during this period.

Our evidence indicates that this migration-fear accuracy penalty reflects information access frictions between Non-White analysts and firms, while explanations based on cognitive constraints, workload differences, or fear-induced pessimism receive little empirical support. Consistent with migration fear heightening out-group distrust and reducing information sharing, the adverse effects on accuracy are concentrated among firms for which private information is more valuable and where

[16] Untabulated regressions of *MFear* on standard macroeconomic indicators (including *EPU*, *VIX*, net migration flows, GDP growth, and unemployment) show that none of the individual coefficients are statistically significant. Although these variables jointly explain a modest share of the variation in *MFear* (adjusted $R^2 = 0.18$), the absence of robust individual associations suggests that *MFear* reflects a distinct dimension of migration-related societal sentiment rather than any single macroeconomic condition.

out-group biases are likely to be salient, including firms led by White CEOs and firms headquartered in non-sanctuary jurisdictions. We further show that migration fear is associated with reduced participation by Non-White analysts in earnings conference calls, and that diminished access to this information channel coincides with larger forecast errors; in response, Non-White analysts appear to rely more heavily on the consensus forecast during high-fear periods.

To our knowledge, this study is the first to document that societal migration fear affects information production by financial analysts. While prior work has examined discrimination in lending and labor markets, we show that sociopolitical frictions can also permeate the information discovery process itself. By impairing the accuracy of Non-White analysts, heightened migration fear may hinder minority career advancement and increase forecast dispersion, with potential implications for market-wide price discovery.

Appendix A. Migration Fear, Private Information Access and the Forecast Accuracy Gap

We develop a simple illustrative example with the sole intention of motivating our empirical predictions and sharpening the intuition behind our conjectures. Our intention is not to develop a fully specified analytical model. Below, our example demonstrates how societal migration fears that erode trust in out-group minorities and restrict their private information access can lead to forecast accuracy gaps between white and non-white analysts that are moderated by migration fear.

A.1 Environment

Consider a firm who will reveal earnings per share, EPS, at an upcoming announcement. The earnings realization is composed of a public information component (μ), a private information component (θ), and an unresolvable random shock (ε):

$$EPS = \mu + \theta + \varepsilon \tag{5}$$

- μ: **Public Information**. Represents non-exclusive common information such as the analysts' consensus, historical data, macro and industry-level information.
- θ: **Private Information**. Represents specific non-public insights. $\theta \sim N(0, \sigma_\theta^2)$.[17]
  - σ_θ^2: The variance in the realization of the private information captures the importance of exclusive insights within the firm's information environment
- ε: **Unresolvable Uncertainty**. Represents random shocks that cannot be predicted by any party (e.g., exogenous news whether systematic or idiosyncratic). $\varepsilon \sim N(0, \sigma_\varepsilon^2)$.
- P: The firm's stock price at the beginning of the quarter.

A.2 Xenophobia and Information Access

We classify analysts as $j \in \{W, NW\}$ (White, Non-White). The firm's CEO controls access to channels that reveal θ. Out-group dynamics across the panel arise because the overwhelming majority of firms in our sample are led by White CEOs (about 95% of EPS forecasts). Following Bowles (2009); Hamilton (1964); Trivers (1971), we model **Societal Migration Fear (Φ)** as a friction that reduces trust in out-group members, limiting their access.

Thus, the impact of analysts' race and societal fears regarding migration on the probability that a firm granting an analyst "Private Information" (λ) can be written as:

$$\lambda_{NW}(\Phi) = \bar{\lambda} - \beta\Phi \quad \text{(Reduced Trust w/Increased Migration Fear for Out-Group)} \tag{6}$$

$$\lambda_W = \bar{\lambda} \quad \text{(Unaffected by Increased Migration Fear for In-Group; } \beta = 0 \text{)} \tag{7}$$

Where $\beta > 0$ represents the sensitivity of the CEO's bias to migration fear, and Φ represents the level of societal migration fear. We note that this linear specification is intended as an illustrative

[17] We are agnostic about the source of θ, which represents any informational advantage from direct access to management. This includes explicit private disclosures ("tipping"), "soft" information conveyed through private channels, or "interactive insight" gained by asking targeted questions in public forums such as conference calls and investor days (Mosaic Theory).

local approximation; parameter values and the empirically relevant range of Φ are such that $0 \leq \lambda_j(\Phi) \leq 1$ over the domain of interest.

A.3 The Analyst's Forecast

The analyst issues a forecasted EPS ($FEPS_j$) based on their information set:

- **Scenario A (Access Granted):** Analyst gains access to management and learns θ. Since ε is unresolvable, the best forecast is:

$$FEPS_j = \mu + \theta \tag{8}$$

- **Scenario B (Access Denied):** Analyst must rely only on common public info μ.

$$FEPS_j = \mu \tag{9}$$

A.4 The Analyst's Forecast Error

The analyst's forecast error (AFE_j) is measured as the absolute value of the most recent forecasted EPS less the actual EPS scaled by the beginning of quarter price, consistent with the empirical design in Section 3:

$$AFE_j = \frac{|FEPS_j - EPS|}{P} \tag{10}$$

Thus, analyst j's realized AFE in each scenario is:

- If Access (Pr $= \lambda$): $AFE_j = \frac{|\varepsilon|}{P}$ (Low Error)
- If No Access (Pr $= 1 - \lambda$): $AFE_j = \frac{|\theta+\varepsilon|}{P}$ (High Error)

Analyst j's expected AFE is the weighted average where
$L = E[|\varepsilon|]$ (Low Error) and $H = E[|\theta + \varepsilon|]$ (High Error), where $H > L$.

$$E[AFE_j] = \frac{1}{P}\left[\lambda_j(\Phi)L + (1 - \lambda_j(\Phi))H\right] \tag{11}$$

Because the error without private information access (H) is strictly higher than the error with access (L), any decrease in access (λ) shifts weight to the higher error state, increasing the total expected AFE.

A.5 Empirical Implications

Given the White analysts' access probability $\lambda_W = \bar{\lambda}$ is fixed, their expected AFE is independent of Migration Fear (Φ).

$$\frac{\partial E[AFE_W]}{\partial \Phi} = 0 \tag{12}$$

The core insight from this basic example, therefore, relates to the out-group, whose access is governed by $\lambda_{NW}(\Phi)$:

A.5.1 Migration Fear increases Forecast Error for Non-White Analysts.

Substituting $\lambda_{NW} = \bar{\lambda} - \beta\Phi$:

$$\frac{\partial E[AFE_{NW}]}{\partial \Phi} = \frac{\beta}{P}(H - L) > 0 \tag{13}$$

Table 2 finds the coefficient on $MFear \times Non\text{-}White$ to be positive and significant, consistent with the idea that Migration fear reduces the probability of the "Low Error" state and increases the probability of the "High Error" state.

A.5.2 Heterogeneity in Xenophobic Sensitivity.

We posit that the sensitivity parameter to societal migration fear β can vary cross-sectionally across firms, i.e. by out-group status Hamilton (1964); Trivers (1971); Baker and Bader (2022), political views Baker and Bader (2022), and sanctuary designated areas Casellas and Wallace (2020), thereby resulting in differential impact of the $MFear \times Non\text{-}White$ coefficient across subsamples.

- **Higher Sensitivity to Φ:** White CEOs, Republican CEOs, or Non-Sanctuary locations ($\beta_H > 0$).
- **Lower Sensitivity to Φ** Non-White CEOs, Democratic CEOs, or Sanctuary locations ($\beta_L < \beta_H$).

Analyses in Table 4 document that the coefficient on $MFear \times Non\text{-}White$ is either highly attenuated or disappears completely in low-bias environments.

A.5.3 Importance of Private Information Amplifies Migration Fear Impact.

$$\frac{\partial^2 E[AFE_{NW}]}{\partial \Phi \partial \sigma_\theta} = \frac{\beta}{P} \cdot \sqrt{\frac{2}{\pi}} \cdot \frac{\sigma_\theta}{\sqrt{\sigma_\theta^2 + \sigma_\varepsilon^2}} > 0 \tag{14}$$

Since all terms on the RHS are positive, the cross-partial is strictly positive, confirming that the importance of information asymmetries between those with information access and those who rely only on public information will amplify the impact of migration fear on forecast error. The Non-White analyst accuracy gap depends on $(H - L)$, which is a function of σ_θ (the volatility of private information).[18] Table 5A finds results consistent with these conjectures, as $MFear \times Non\text{-}White$ is positively associated with firms that have high idiosyncratic volatility.

A.5.4 Conference Call Access as Mechanism Validation

A central assumption of our story is that the increase in Non-White forecast error is driven by a reduction in information access (λ) rather than a degradation of ability. While we do not observe management access directly, we can proxy for λ using Conference Call Participation (Table 5B/5C). Consistent with the prediction that $\partial\lambda/\partial\Phi < 0$, Non-White analysts are significantly less likely

[18] In our setting, σ_θ determines the influence of the private signal (θ) in the firm's information environment. A high σ_θ implies a wide distribution of private information, so the typical draw of θ is large and the informational stakes are high. Excluding the Non-White analyst would then imposes a much larger penalty (a wider $H - L$ gap) than when σ_θ is low, i.e. migration fear has the largest impact on Non-White analysts precisely when informational stakes are highest.

to participate in conference calls during periods of high migration fear. This evidence provides additional support for the "Access Friction" channel as the primary driver of our results.

A.5.5 Migration Fear Amplifies Herd Behavior for Non-White Analysts.

Recall that "Public Information" (μ) represents the consensus belief. When access is denied, the analyst's forecast collapses to $FEPS_j = \mu$. Therefore, as migration fear rises and access is more restricted, Non-White analysts will increasingly discard idiosyncratic private signals and simply output the consensus. Table 6 finds Non-White analysts are significantly more likely to "herd" towards the consensus during periods of high migration fear.

Appendix B. Variable Definitions

Analyst-Level Variables

Variable	Definition
AFE	Analyst absolute forecast error, determined as the absolute difference between the analyst's EPS forecast and the actual EPS, scaled by the stock price at the start of the firm's fiscal quarter.
Analyst Experience	Logged number of years the analyst has been recorded in the IBES database.
Analyst Portfolio	Logged number of firms that the analyst is following in the same forecasting year-quarter period.
Brokerage Size	Logged number of analysts at the brokerage house with which the analyst is affiliated in the forecasting year-quarter period.
CC Participation	Indicator variable for analyst participation in earnings call Q&A.
Female	An indicator equal to one if the analyst is a female.
Herding	An indicator variable when the forecast revision moves between the analyst's own prior forecast and the consensus estimate.
Horizon	Logged number of days between the firm's fiscal date and the analyst's forecast date.
Last Minute Forecast	An indicator variable when the forecast revision is issued in the final 1–6 calendar days prior to the earnings announcement.
Lead–Follow Ratio	The ratio of the cumulative number of days by which the preceding two forecasts lead the forecast of interest to the cumulative number of days by which the subsequent two forecasts follow the forecast of interest.
Non-White	An indicator equal to one if the analyst is Black, Hispanic or Asian. It is inferred by using the NamePrism algorithm.
Signed FE	Determined as the difference between the Analyst's EPS forecast and the actual EPS.

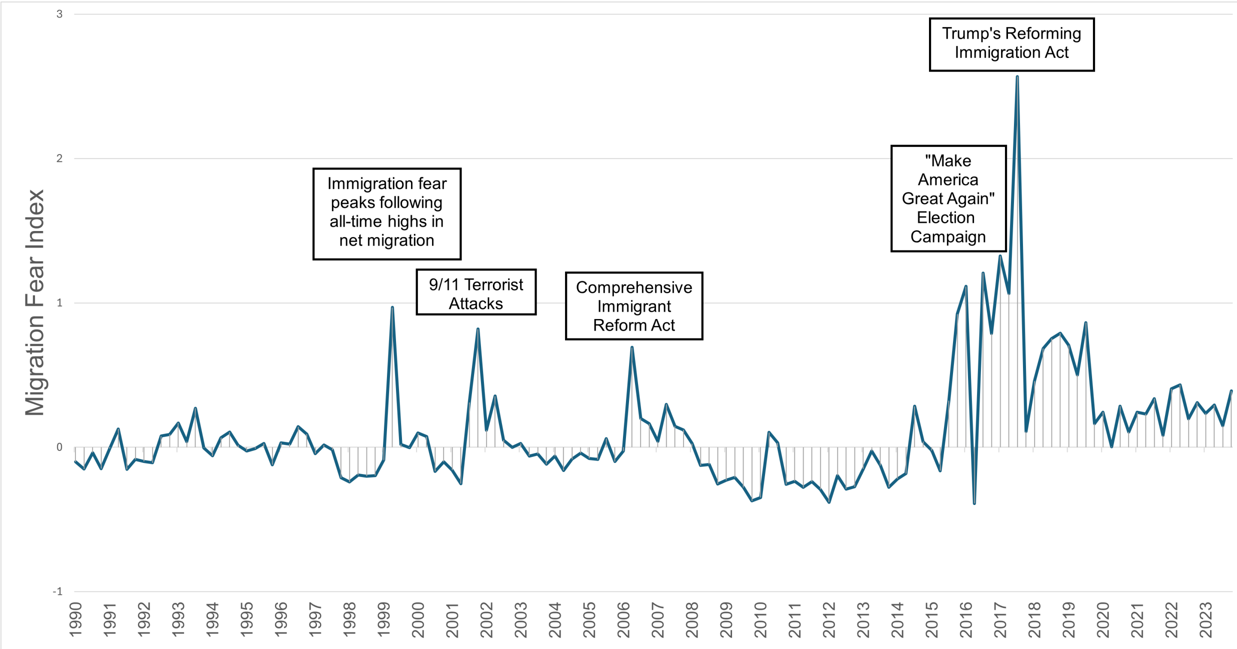
Firm-Level Variables

Idiosyncratic Volatility	Residual volatility from a Fama-French plus Momentum Four-factor Asset Pricing Model using a 36-month (minimum of 24-month) rolling window and updated monthly.
Non-White CEO	An indicator equal to one if a firm has a non-white CEO, obtained from Rupar, Wang and Yoon (2024).
Number of Analysts	Logged number of analysts following the same company in each forecasting year-quarter period.
Republican CEO	Indicator variable for the CEO based on the majority of their political contributions.
Sanctuary	An indicator equal to one if a firm is headquartered in a sanctuary county.
Size	Logged market capitalization at the firm's fiscal quarter-end.
Tobin's Q	The sum of the market value of equity and the book value of assets less the book value of equity, all scaled by the book value of assets. The stock price used to calculate the market value of equity is as of the firm's fiscal quarter-end.

Macro-Level Variables

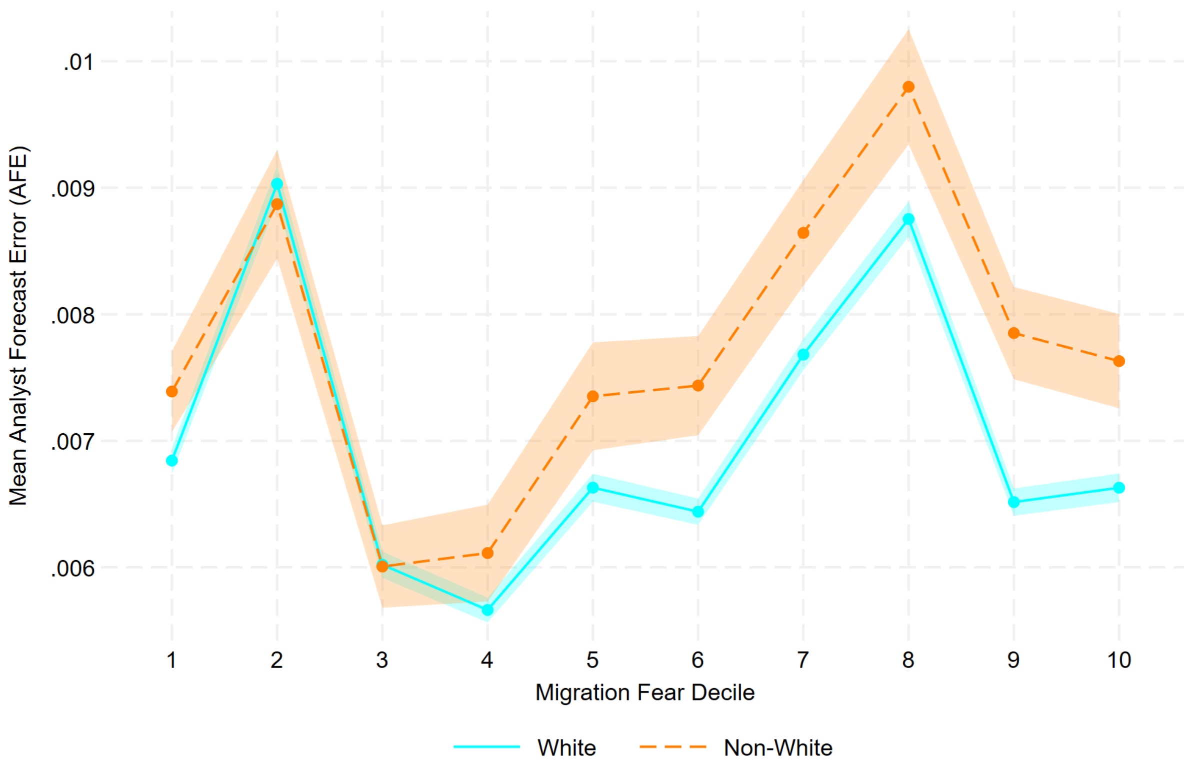
EPU	Economic Policy Uncertainty Index, developed by Baker et al. (2016), quantifies uncertainty in U.S. economic policy.
GDP	Logged value of quarterly U.S. GDP, expressed in billions of current dollars.
MFear	The Baker et al. (2016) Migration Fear Index, normalized over the sample period to mean = 0, standard deviation = 1. This index gauges the proportion of newspaper articles containing predefined terms related to migration and fear relative to the total articles published in the same calendar quarter. The migration related terms include "immigration, migration, assimilation, migrant, immigrant, asylum, refugee, open borders, border control, Schengen, and human trafficking," while the fear-associated terms consist of "anxiety, panic, bomb, fear, crime, terror, worry, concern, and violent."
MFear Gallup	Standardized value (mean = 0, standard deviation = 1) of the monthly Gallup's poll of public opinion and attitudes towards immigrants.
Net Migration	Logged value of the quarterly U.S. net migration rate.
PostCampaign	Indicator variable that equals 1 for forecasts issued in 2016-2019 and equals 0 for forecasts issued in 2011-2014.
Unemployment	U.S. unemployment rate, reported quarterly.
VIX	Chicago Board Options Exchange (CBOE) volatility index, reported as the quarterly average, measures implied equity market volatility.

Figure 1: US Migration Fear Index



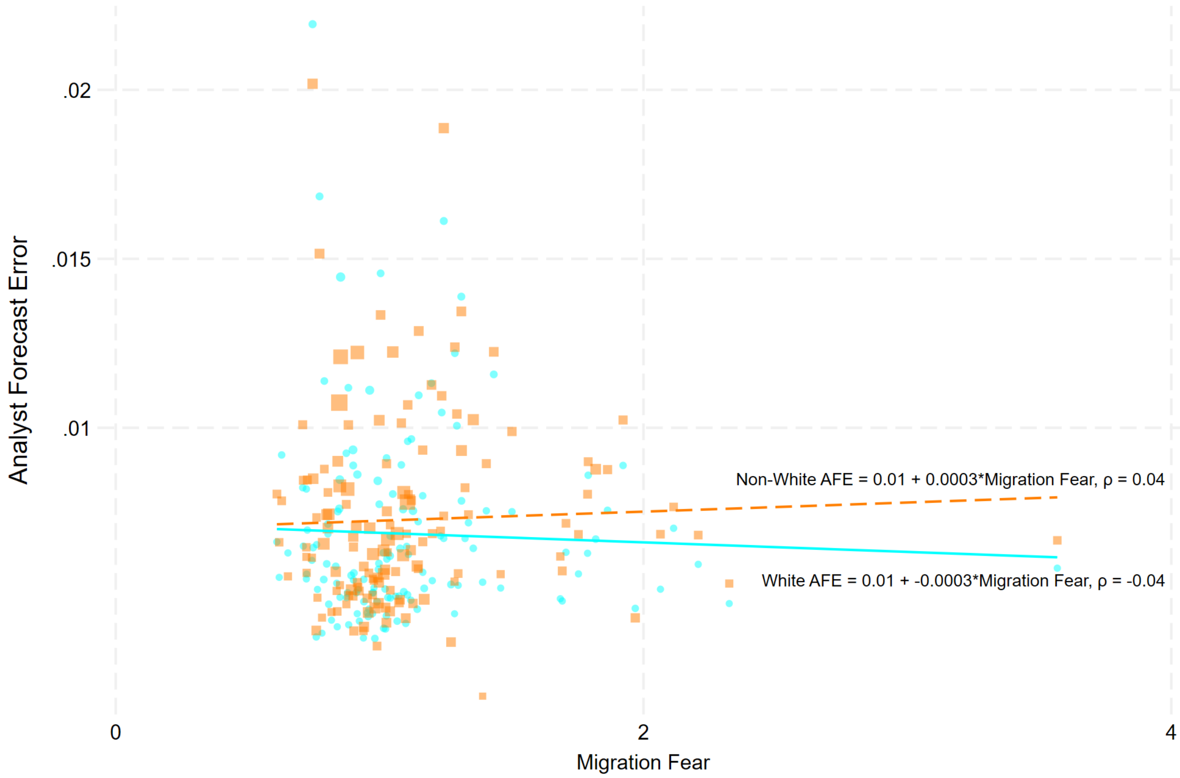
This line graph displays the U.S. Migration Fear Index, adapted from Baker et al. (2016), spanning from 1990 to 2023. The index is standardized (mean = 0, standard deviation = 1) to illustrate time-series variation in migration-related fears over time. Key spikes in the index align with notable policy events and crises, highlighted by labeled text boxes.

Figure 2: Migration Fear and Analyst Forecast Errors by Decile Ranks of Migration Fear



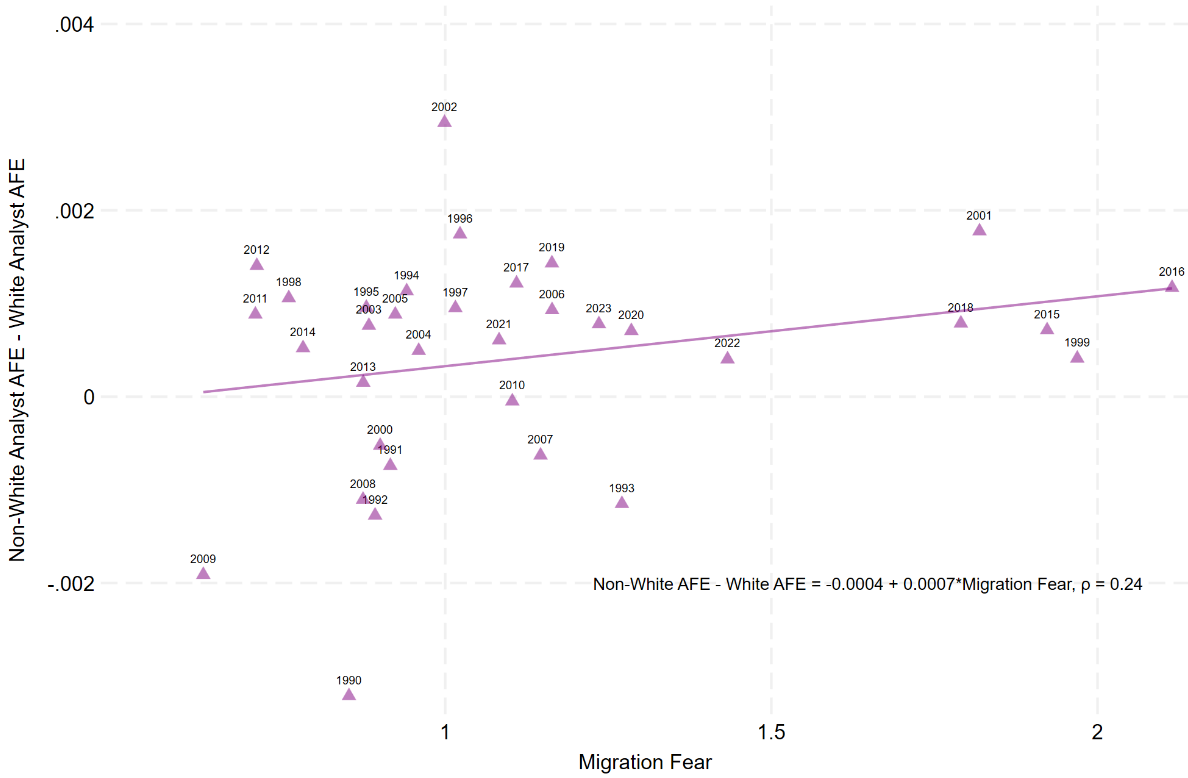
This line graph illustrates the Mean Absolute Analyst Forecast Error (AFE) for White and Non-White analysts across ranked deciles of the Migration Fear index, based on quarterly earnings announcements from 1990 to 2023. The solid aqua line represents White analysts' AFE, while the dotted orange line represents Non-White analysts' AFE. Shaded bands around each line indicate 95% confidence intervals. The gap between the shaded bands reveals that Non-White analysts exhibit a notable increase in forecast error in the higher deciles of Migration Fear compared to White analysts, suggesting a potential differential impact of migration sentiment on forecast accuracy by analyst ethnicity.

Figure 3: Migration Fear and Analyst Forecast Error by Race



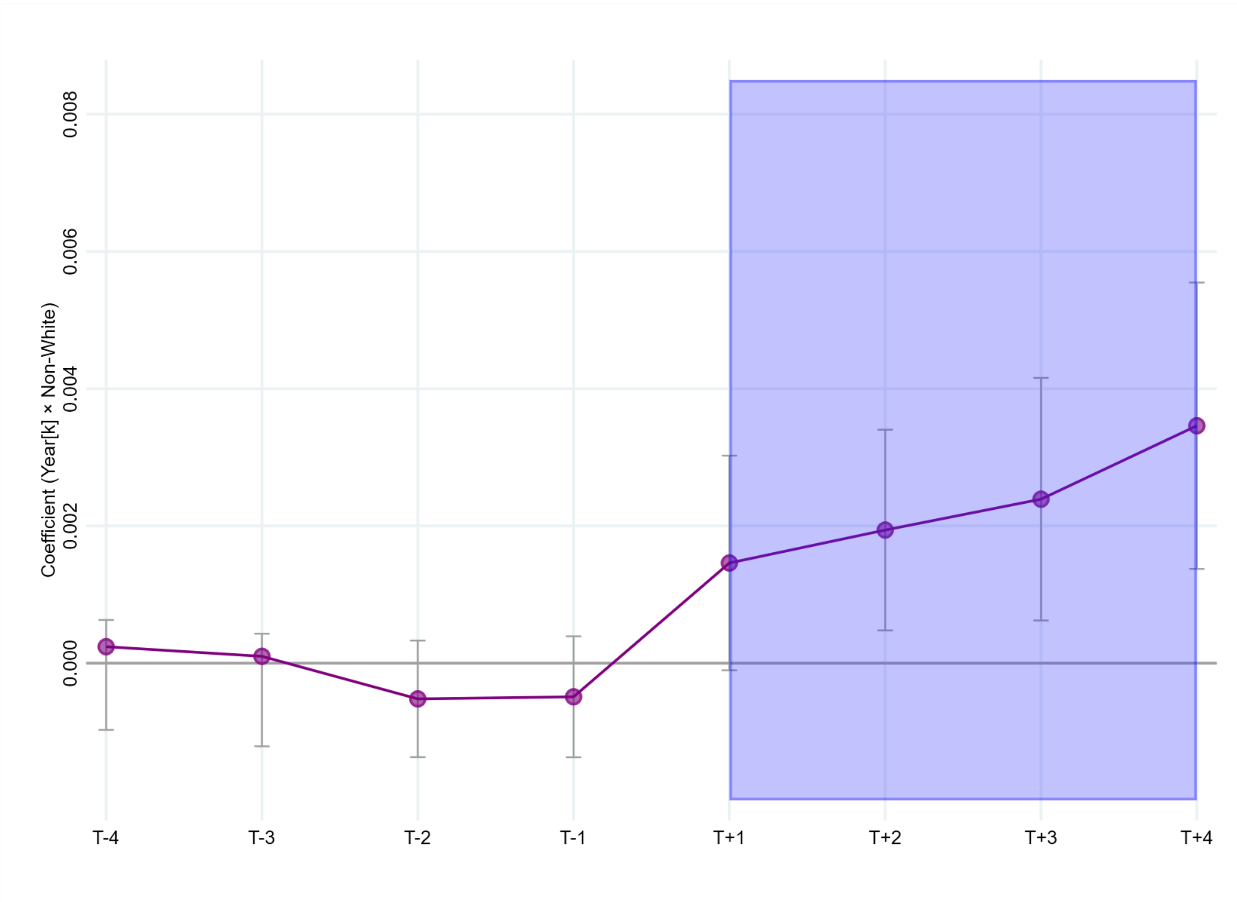
The scatterplot depicts the relationship between the quarterly Mean AFE and the Migration Fear index, segmented by analyst ethnicity (*Non-White* and *White*) across earnings announcements from 1990 to 2023. *Non-White AFE* values are represented by orange squares, while *White AFE* values are shown as aqua circles. Each point's size is proportional to the standard error within the respective year-quarter. The dotted orange line (solid aqua line) indicates the linear fit for *Non-White AFE* (*White AFE*). Slope and correlation coefficient (ρ) are tabulated for each group.

Figure 4: US Migration Fear Index and Disparities in Analyst Forecast Error by Year



The scatterplot depicts the relationship between the Migration Fear index and the annual race-based analyst accuracy gap, measured across (*Non-White* and *White*) Mean *AFE* from 1990 to 2023. The straight line indicates the linear fit for *(Non-White AFE - White AFE)* and *Migration Fear*. Note: The slope in this figure is estimated using annual Non-White minus White mean AFE and is not intended to equal the difference between the year-quarter group-specific slopes reported in Figure 3.

Figure 5: Impact of Donald Trump's (2016) Presidential Election Campaign on Non-White Analyst Forecast Error



This figure illustrates the regression coefficients for each interaction term between *Year[k] and Non-White*, derived from the following equation, where *Year[k]* is an indicator variable that equals 1 in year k:

$$AFE_{ijt} = \sum \beta_k Year_k \times Non-White + \gamma^{'} \boldsymbol{X} + FE_{Firm-Analyst} + \varepsilon_{ijt} \tag{15}$$

Year ranges from 2011-2014 (pre-Campaign period) and 2016-2019 (post-Campaign period).Error bars represent 95% confidence intervals of the coefficients.

Table 1: Descriptive Statistics

This table presents descriptive statistics, including the number of firm-quarter observations, sample mean, standard deviation, lower quartile, median, and upper quartile. Detailed definitions for all variables are provided in Appendix A.

Variable	N	Mean	Std Dev	Q1	Median	Q3
AFE	1,360,603	0.007	0.021	0.001	0.002	0.005
Non-White	1,360,603	0.119	0.324	0.000	0.000	0.000
MFear	1,360,603	0.000	1.000	-0.671	-0.258	0.319
MFear Gallup	1,360,603	0.000	1.000	-0.604	0.140	0.706
Size	1,360,603	7.917	1.896	6.598	7.905	9.214
Tobin's Q	1,360,603	2.298	1.731	1.229	1.704	2.647
Female Analyst	1,360,603	0.092	0.289	0.000	0.000	0.000
Analyst Exp	1,360,603	2.179	0.770	1.792	2.303	2.773
Horizon	1,360,603	3.690	0.732	3.497	3.989	4.143
Brokerage Size	1,360,603	2.886	1.002	2.303	3.091	3.611
# of Analysts	1,360,603	1.757	0.834	1.099	1.792	2.398
Analyst Portfolio	1,360,603	2.545	0.543	2.303	2.639	2.890

Table 2: Baseline Results

This table reports the coefficient estimates from ordinary least squares regressions, examining the interaction between the migration fear index (MFear) and the Non-White indicator on analyst absolute forecast error (AFE). Non-White is an indicator variable equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian, while MFear represents the migration fear index developed by Baker, Bloom, and Davis (2015, 2016). Columns (1) - (4) provide baseline regression results with various fixed-effects. Columns (5)–(8) introduce additional interaction terms with MFear to capture effects across various analyst and firm characteristics, including Size, Tobin's Q, gender, experience, forecast horizon, brokerage size, number of analysts, and analyst portfolio size. Control variable definitions are provided in the appendix. The Adj R2: MFear x NW is a regression diagnostic from Armstrong et al (2022) when high dimension fixed effects are used, calculated adjusted R2 from the regression of MFear $\times$ Non-White on fixed effects alone. Variance inflation factors (VIF) for the interaction term are provided to check multicollinearity. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

Table 2. Baseline Results (continued)

	(1)	(2)	(3)	(4)
VARIABLES		AFE		
$MFear \times Non-White$	0.00061***	0.00062***	0.00057***	0.00059***
	(3.78)	(3.56)	(3.20)	(3.17)
$MFear$	-0.00013	-0.00013	-0.00017	-0.00012
	(-0.86)	(-0.88)	(-0.81)	(-0.85)
$Non-White$	0.00022*			
	(1.86)			
$Size$	-0.00233***	-0.00239***	-0.00236***	-0.00329***
	(-13.14)	(-13.55)	(-10.96)	(-13.69)
$Tobin'sQ$	-0.00187***	-0.00186***	-0.00198***	-0.00189***
	(-20.65)	(-22.07)	(-17.81)	(-22.70)
$Female$	0.00022**			
	(2.41)			
$AnalystExp$	0.00007	0.00011	0.00300***	0.00087***
	(1.25)	(0.71)	(8.31)	(3.78)
$Horizon$	0.00026***	0.00026***	0.00022*	0.00031***
	(3.93)	(3.95)	(1.94)	(4.55)
$BrokerageSize$	-0.00009**	-0.00003	-0.00053***	0.00007
	(-2.03)	(-0.39)	(-3.48)	(0.53)
$\#ofAnalysts$	-0.00144***	-0.00151***	-0.00158***	-0.00119***
	(-7.99)	(-8.28)	(-7.28)	(-6.73)
$AnalystPortfolio$	0.00019***	0.00027***	0.00062***	0.00035***
	(2.79)	(2.87)	(4.60)	(3.25)
Observations	1,347,842	1,347,806	1,336,210	1,336,210
# of Fixed Effects	11,839	15,430	104,945	104,978
Adjusted R^2	0.414	0.420	0.467	0.475
Adjusted $R^2(MFearxNW)$	0.098	0.112	0.128	0.195
VIF (MFear x NW)	1.204	1.388	1.679	1.681
Year FE	YES	YES	NO	YES
Firm FE	YES	YES	NO	NO
Analyst FE	NO	YES	NO	NO
Firm X Analyst FE	NO	NO	YES	YES

Table 2. Baseline Results (continued)

	(5)	(6)	(7)	(8)
VARIABLES		AFE		
$MFear \times Non-White$	0.00055***	0.00057***	0.00056***	0.00055***
	(3.88)	(3.66)	(3.39)	(3.28)
$MFear$	0.00058	0.00026	-0.00123	-0.00020
	(0.77)	(0.36)	(-1.37)	(-0.29)
$Non-White$	0.00023*			
	(1.97)			
$Size$	-0.00236***	-0.00242***	-0.00239***	-0.00331***
	(-13.10)	(-13.54)	(-10.95)	(-13.73)
$Tobin'sQ$	-0.00187***	-0.00186***	-0.00198***	-0.00188***
	(-20.50)	(-21.85)	(-17.78)	(-22.41)
$Female$	0.00021**			
	(2.41)			
$AnalystExp$	0.00007	0.00014	0.00310***	0.00089***
	(1.30)	(0.90)	(8.62)	(3.87)
$Horizon$	0.00025***	0.00026***	0.00022*	0.00030***
	(3.84)	(3.90)	(1.91)	(4.51)
$BrokerageSize$	-0.00009**	-0.00003	-0.00051***	0.00007
	(-2.02)	(-0.37)	(-3.35)	(0.56)
$\#of Analysts$	-0.00142***	-0.00149***	-0.00157***	-0.00118***
	(-7.73)	(-8.07)	(-7.14)	(-6.61)
$AnalystPortfolio$	0.00019***	0.00027***	0.00062***	0.00036***
	(2.77)	(2.85)	(4.50)	(3.22)
$MFear \times Size$	-0.00017**	-0.00014**	-0.00006	-0.00008
	(-2.38)	(-2.13)	(-1.02)	(-1.30)
$MFear \times Tobin'sQ$	0.00003	0.00005	0.00009	0.00008
	(0.49)	(0.75)	(1.25)	(1.17)
$MFear \times Female$	-0.00011	-0.00014	-0.00013	-0.00015
	(-1.11)	(-1.35)	(-1.18)	(-1.35)
$MFear \times AnalystExp$	-0.00001	0.00004	0.00027**	0.00003
	(-0.12)	(0.78)	(2.22)	(0.51)
$MFear \times Horizon$	-0.00009	-0.00007	-0.00005	-0.00005
	(-1.31)	(-1.13)	(-0.75)	(-0.92)
$MFear \times BrokerageSize$	0.00005	0.00007	0.00009	0.00007
	(1.04)	(1.43)	(1.58)	(1.27)
$MFear \times \#of Analysts$	0.00029**	0.00024*	0.00014	0.00016
	(2.13)	(1.90)	(1.53)	(1.50)
$MFear \times Portfolio$	0.00009	0.00006	0.00001	0.00007
	(1.14)	(0.77)	(0.05)	(0.79)
Observations	1,347,842	1,347,806	1,336,210	1,336,210
# of Fixed Effects	11,748	15,105	103,455	103,591
Adjusted R^2	0.415	0.420	0.467	0.475
Adjusted $R^2(MFearxNW)$	0.098	0.112	0.128	0.195
VIF (MFear x NW)	1.204	1.388	1.679	1.681
Year FE	YES	YES	NO	YES
Firm FE	YES	YES	NO	NO
Analyst FE	NO	YES	NO	NO
Firm x Analyst FE	NO	NO	YES	YES

Table 3: Pre-Post 2015-2016 Presidential Election Campaign

This table reports the coefficient estimates from ordinary least squares regressions, analyzing the interaction between the *PostCampaign* period and the *Non-White* indicator on analyst absolute forecast error (*AFE*). *Non-White* is an indicator variable equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. The regression sample includes forecasts issued during the four years before and four years after the start of Trump's "Make America Great Again" presidential campaign in June 2015, with year 2015 left out of the sample for clear pre-post identification purposes. *PostCampaign* is an indicator variable the equals 1 for forecasts issued in 2016-2019, and equals 0 for forecasts issued in 2011-2014. Control variable definitions are provided in the appendix. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

VARIABLES	(1) AFE
Non-White × *PostCampaign*	0.00344***
	(4.81)
PostCampaign	0.00116***
	(3.19)
Size	-0.00308***
	(-9.61)
Tobin's Q	-0.00182***
	(-17.86)
Analyst Exp	0.00141**
	(2.12)
Horizon	0.00024***
	(3.22)
Brokerage Size	-0.00000
	(-0.02)
# of Analysts	-0.00142***
	(-4.23)
Analyst Portfolio	0.00016
	(1.09)
Observations	434,751
Adjusted R^2	0.531
Firm × Analyst FE	YES

Table 4: Heterogeneity in Out-Group Bias, Migration Fear and AFE

This table presents coefficient estimates from ordinary least squares regressions on analyst absolute forecast error (*AFE*) across various sample splits related to firm characteristics and the regulatory environment. *Sanctuary* is an indicator equal to one if the forecast is for a firm headquartered in a sanctuary city or county. CEO ethnicity and CEO political affiliation distinguish forecasts for firms led by *Non-White CEOs* and *White CEOs*, and *Republican CEOs* and *Democratic CEOs* . The interaction term *MFear* × *Non-White* captures the effect of the migration fear index (*MFear*) on forecast errors for Non-White analysts, where Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Control variable definitions are provided in the appendix. Firm-by-analyst and year fixed effects are included in each specification. P-values from coefficient equality tests (Wald Test) are reported to assess statistical differences across the splits. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

VARIABLES	(1) Non-White CEO	(2) White CEO	(3) Sanctuary	(4) Non-Sanctuary	(5) Republican CEO	(6) Democratic CEO
MFear × *Non-White*	-0.00006	0.00050***	0.00005	0.00022***	0.00087***	0.00038**
	(-0.31)	(3.16)	(0.65)	(3.13)	(4.93)	(2.43)
MFear	-0.00031*	-0.00007	0.00003	-0.00005	-0.00006	-0.00004
	(-1.68)	(-0.67)	(0.60)	(-0.84)	(-0.46)	(-0.28)
Size	-0.00120***	-0.00236***	-0.00039	-0.00058***	-0.00265***	-0.00204***
	(-3.07)	(-9.83)	(-1.35)	(-3.96)	(-7.79)	(-5.89)
Tobin's Q	-0.00092***	-0.00136***	-0.00102***	-0.00080***	-0.00180***	-0.00139***
	(-5.58)	(-16.46)	(-11.66)	(-15.04)	(-12.53)	(-13.96)
Analyst Exp	0.00128*	0.00040*	0.00013	0.00014	0.00053**	0.00062
	(1.86)	(1.76)	(0.63)	(0.65)	(2.00)	(1.49)
Horizon	-0.00002	0.00018***	0.00009**	0.00012***	0.00021***	0.00028***
	(-0.12)	(3.88)	(2.09)	(3.78)	(2.81)	(3.90)
Brokerage Size	0.00039	-0.00002	-0.00009	-0.00018*	0.00014	-0.00011
	(1.39)	(-0.13)	(-0.84)	(-1.67)	(1.34)	(-0.41)
# of Analysts	-0.00073*	-0.00113***	-0.00041**	-0.00054***	-0.00084***	-0.00098***
	(-1.71)	(-5.83)	(-2.17)	(-3.95)	(-3.68)	(-3.73)
Analyst Portfolio	0.00016	0.00014	-0.00002	0.00014	0.00012	0.00030
	(0.47)	(1.39)	(-0.21)	(1.37)	(0.77)	(1.65)
Observations	27,336	595,066	208,328	435,449	353,038	329,544
R^2	0.400	0.383	0.396	0.448	0.523	0.508
Firm X Analyst FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
F-test (P-value)	0.02		0.07		0.03	

Table 5A: Relative Importance of Public vs. Private information

This table presents coefficient estimates from ordinary least squares regressions on analyst absolute forecast error (AFE), examining the relative importance of public versus private information for firms with different levels of macro factor co-movement and private information. The sample is split based on whether the forecast is issued for a firm with high vs low idiosyncratic volatility. Firm-specific idiosyncratic volatility (Ivol) is calculated for each firm based on residuals from a 4-factor model. Ivol is calculated using a 36-month (minimum of 24-month) rolling window and is updated monthly; the annual average of monthly Ivol is used to split the sample. The interaction term MFear × Non-White captures the effect of the migration fear index (MFear) on forecast errors for Non-White analysts. MFear represents the migration fear index by Baker, Bloom, and Davis (2015, 2016), while Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Control variable definitions are provided in the appendix. Each regression includes firm-by-analyst and year fixed effects. P-values from coefficient equality tests are shown to assess statistical differences across the splits. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

	(1)	(2)
	Idiosyncratic Volatility	
VARIABLES	≤ Median	> Median
MFear × Non-White	0.00009	0.00075***
	(1.47)	(3.24)
MFear	-0.00004	-0.00015
	(-1.06)	(-0.69)
Size	-0.00017	-0.00472***
	(-1.38)	(-13.45)
Tobin's Q	-0.00048***	-0.00218***
	(-12.62)	(-22.44)
Analyst Exp	0.00019*	0.00112***
	(1.69)	(2.86)
Horizon	0.00010***	0.00046***
	(3.86)	(4.07)
Brokerage Size	0.00006	0.00005
	(1.44)	(0.25)
# of Analysts	-0.00015*	-0.00131***
	(-1.88)	(-5.76)
Analyst Portfolio	-0.00001	0.00060***
	(-0.16)	(3.30)
Observations	557,637	771,826
Adjusted R^2	0.392	0.531
Firm × Analyst FE	YES	YES
Year FE	YES	YES
F-test (P-value)	0.0035	

Table 5B: Migration Fear and Conference Call Participation

This table presents coefficient estimates from logistic regressions on conference call participation, examining the interaction between migration fear (MFear) and the Non-White indicator for analysts. The dependent variable, CC Participation is an indicator variable that equals to one if an analyst is included in the *Q & A* session of an earning conference call. The interaction term MFear × Non-White represents the effect of the migration fear index (MFear), developed by Baker, Bloom, and Davis (2015, 2016), where Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black Hispanic, or Asian. Control variable definitions are provided in the appendix. Z-statistics are shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

VARIABLES	(1) CC Participation
MFear × Non-White	-0.05746***
	(-5.79)
Non-White	-0.10983***
	(-10.46)
MFear	0.00773**
	(2.03)
Size	-0.24738***
	(-96.45)
Tobin's Q	-0.00391*
	(-1.90)
Female	-0.15158***
	(-11.30)
Analyst Exp	0.22871***
	(39.28)
Horizon	0.16494***
	(28.57)
Brokerage Size	0.40106***
	(88.82)
# of Analysts	0.40042***
	(69.23)
Analyst Portfolio	0.34060***
	(40.92)
Observations	1,357,856
Pseudo R^2	0.079

Table 5C: Conference Call Participation and AFE

This table presents coefficient estimates from ordinary least squares regressions on analyst absolute forecast error (AFE) with sample split based on whether the analyst participated in earnings conference call of the firm-quarter. CC Participated is an indicator variable set to one if the analyst is invited to ask question during the conference call in the firm-quarter of the forecast. The interaction term MFear × Non-White captures the effect of the migration fear index (MFear) on forecast errors for Non-White analysts. MFear represents the migration fear index by Baker, Bloom, and Davis (2015, 2016), while Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Control variable definitions are provided in the appendix. Each regression includes firm-by-analyst and year fixed effects. P-values from coefficient equality tests are shown to assess statistical differences across the splits. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

	(1)	(2)
	CC Participated	
VARIABLES	= 1	= 0
MFear × Non-White	0.00033**	0.00091***
	(2.21)	(3.99)
MFear	-0.00011	-0.00021
	(-0.57)	(-0.46)
Size	-0.00311***	-0.00344***
	(-13.11)	(-12.19)
Tobin's Q	-0.00098***	-0.00333***
	(-20.11)	(-24.11)
Analyst Exp	0.00451***	0.00021**
	(3.44)	(2.02)
Horizon	0.00053***	0.00021***
	(5.11)	(4.10)
Brokerage Size	0.00001	0.00191
	(0.51)	(0.58)
# of Analysts	-0.00192***	-0.00088***
	(-8.11)	(-5.22)
Analyst Portfolio	0.00031***	0.00040**
	(3.77)	(2.12)
Observations	502,406	855,450
Adjusted R^2	0.400	0.383
Firm × Analyst FE	YES	YES
Year FE	YES	YES
F-test (P-value)	0.061	

Table 6: Migration Fear and Analyst Forecast Properties

This table reports coefficient estimates from ordinary least squares regressions examining changes in analysts' behaviors in response to migration fear, with outcomes including herding behavior, lead-follow ratios, and last-minute forecasts. The interaction term MFear $\times$ Non-White captures the effect of the migration fear index (MFear) on forecast behaviors for Non-White analysts. MFear represents the migration fear index developed by Baker, Bloom, and Davis (2015, 2016), and Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Control variable definitions are provided in the appendix. Each regression includes firm-by-analyst and year fixed effects. Standard errors are clustered at the analyst and quarter levels, with t-statistics in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

VARIABLES	(1) Herding	(2) Last Minute	(3) Lead-Follow Ratio
MFear × Non-White	0.020***	0.003**	-0.055***
	(3.42)	(2.20)	(-6.98)
MFear	-0.021*	0.002	0.206***
	(-1.86)	(0.72)	(3.95)
Size	0.010***	-0.003***	-0.009
	(3.58)	(-5.77)	(-0.89)
Tobin's Q	0.005***	0.001***	-0.003
	(5.09)	(3.57)	(-0.87)
Analyst Exp	-0.023***	-0.012***	-0.039**
	(-5.50)	(-8.57)	(-2.07)
Horizon	-0.006**	-0.006***	-0.335***
	(-2.23)	(-9.27)	(-19.49)
Brokerage Size	0.008***	-0.002***	0.017**
	(3.61)	(-3.66)	(2.18)
# of Analysts	-0.109***	-0.005***	-0.279***
	(-32.76)	(-8.59)	(-24.29)
Analyst Portfolio	-0.008***	-0.004***	0.018*
	(-4.17)	(-5.53)	(1.96)
$MFear \times Size$	-0.000	-0.000	-0.004*
	(-0.41)	(-0.06)	(-1.73)
$MFear \times Tobin'sQ$	0.000	-0.000	-0.002
	(0.75)	(-0.09)	(-0.97)
$MFear \times Female$	-0.002	-0.001	-0.004
	(-1.01)	(-1.05)	(-0.39)
$MFear \times AnalystExp$	-0.003***	0.000	-0.001
	(-3.38)	(0.38)	(-0.30)
$MFear \times Horizon$	-0.006***	-0.001	-0.037***
	(-2.78)	(-1.48)	(-3.36)
$MFear \times BrokerageSize$	-0.001	-0.000	0.001
	(-1.26)	(-1.61)	(0.31)
$MFear \times \#ofAnalysts$	0.003*	0.000	-0.010*
	(1.91)	(0.80)	(-1.89)
$MFear \times Portfolio$	0.003**	0.000	-0.000
	(2.23)	(1.32)	(-0.05)
Observations	1,204,514	1,204,514	1,204,514
R^2	0.110	0.125	0.146
Year FE	YES	YES	YES
Firm × Analyst FE	YES	YES	YES

Table 7A: Limited Information Processing Capacity

This table presents coefficient estimates from ordinary least squares regressions on analyst absolute forecast error (AFE), focusing on the effect of limited information processing capacity, as proxied by brokerage size and analyst portfolio size. The sample is split into forecasts issued by analysts at brokerages with above- and below-median sizes, and separately by forecasts issued by analysts managing above- and below-median portfolios. The interaction term MFear × Non-White measures the effect of the migration fear index (MFear) on forecast errors for Non-White analysts, where MFear is the migration fear index by Baker, Bloom, and Davis (2015, 2016), and Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Control variable definitions are provided in the appendix. Each regression includes firm-by-analyst and year fixed effects. P-values from coefficient equality tests are shown to assess statistical differences across the splits. Standard errors are clustered at the analyst and quarter levels, with t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

	(1)	(2)	(3)	(4)
	Brokerage Size		Analyst Portfolio	
	≤ Median	> Median	≤ Median	> Median
MFear × Non-White	0.00054***	0.00059**	0.00023*	0.00066***
	(2.76)	(2.41)	(1.94)	(3.16)
MFear	-0.00017	-0.00007	-0.00013	-0.00012
	(-1.09)	(-0.58)	(-1.08)	(-0.73)
Size	-0.00395***	-0.00281***	-0.00319***	-0.00355***
	(-12.69)	(-10.33)	(-12.90)	(-11.42)
Tobin's Q	-0.00206***	-0.00170***	-0.00182***	-0.00196***
	(-21.02)	(-19.35)	(-22.48)	(-18.90)
Analyst Exp	0.00130***	0.00058	0.00095***	0.00095*
	(4.42)	(1.54)	(4.17)	(1.95)
Horizon	0.00032***	0.00028***	0.00032***	0.00029***
	(3.86)	(4.53)	(3.97)	(4.56)
Brokerage Size	-0.00003	0.00075	0.00031***	-0.00021
	(-0.25)	(1.55)	(3.19)	(-0.75)
# of Analysts	-0.00110***	-0.00122***	-0.00107***	-0.00130***
	(-5.88)	(-5.96)	(-6.10)	(-6.33)
Analyst Portfolio	0.00043***	0.00023	0.00031***	0.00074**
	(3.68)	(1.49)	(2.63)	(2.02)
Observations	697,133	631,655	702,504	615,101
R^2	0.552	0.496	0.553	0.524
Firm × Analyst FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
F-test (P-value)	0.8739		0.6553	

Table 7B: Pessimistic Bias with Signed Forecast Error

This table presents coefficient estimates from ordinary least squares regressions on signed forecast error, examining the interaction between migration fear (MFear) and the Non-White indicator for analysts. The dependent variable, signed forecast error, captures the directional inaccuracy of analyst forecasts. The interaction term MFear × Non-White represents the effect of the migration fear index (MFear), developed by Baker, Bloom, and Davis (2015, 2016), on forecast errors for Non-White analysts, where Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. Regression includes firm-by-analyst and year fixed effects. Control variable definitions are provided in the appendix. Standard errors are clustered at the analyst and quarter levels, with t-statistics shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions can be found in Appendix A.

VARIABLES	(1) Signed FE
MFear × Non-White	0.00002
	(0.26)
MFear	0.00001
	(0.09)
Size	0.00020
	(1.65)
Tobin's Q	-0.00005
	(-0.92)
Analyst Exp	0.00007
	(0.54)
Horizon	0.00014***
	(3.28)
Brokerage Size	-0.00001
	(-0.16)
# of Analysts	0.00024***
	(3.72)
Analyst Portfolio	0.00000
	(0.03)
Observations	1,336,210
Adjusted R^2	0.136
Year FE	YES
Firm × Analyst FE	YES

Table 8: Robustness Tests: Alternative Specifications of Baseline Regression

This table presents coefficient estimates from baseline regressions of analyst absolute forecast error (AFE) on migration fear (*MFear*). Column (1) uses *PMAFE*, the absolute forecast error of an analyst divided by the mean absolute forecast error for the same firm-year-quarter. Column (2) uses OLS on a sample balanced by entropy weighting. Column (3) employs a monthly Gallup Poll on immigration as an alternative *MFear* measure. Column (4) orthogonalizes $MFear$ to macroeconomic uncertainty, regressing it on VIX, net migration, unemployment, and Baker, Bloom, and Davis (2016) Policy Uncertainty indices (economic, monetary, national security, and social). Column (5) orthogonalizes $MFear$ to trade uncertainty using the US Daily and China Trade Policy Uncertainty Indices (Baker et al., 2016). The interaction $MFear \times Non-White$ represents the effect on Non-White analysts, where Non-White is an indicator equal to one if the analyst's inferred ethnicity is Black, Hispanic, or Asian. All regressions include firm-by-analyst and year fixed effects. Standard errors are clustered at the analyst and quarter levels; t-statistics are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

VARIABLES	(1) AFE = $PMAFE$	(2) Entropy Balanced	(3) MFear = *Gallup*	(4) MFear = $\perp_{Macro}$	(5) MFear = $\perp_{Trade}$
MFear × Non-White	0.01147***	0.00054***	0.00036***	0.00966***	0.00956***
	(3.30)	(3.22)	(3.11)	(3.65)	(3.62)
MFear	-0.00040	-0.00025	0.31058***	-0.00040	-0.00042
	(-0.32)	(-1.33)	(4.01)	(-0.37)	(-0.39)
Size	0.00404	-0.00465***	-0.00329***	0.00409	0.00409
	(1.48)	(-11.17)	(-13.70)	(1.50)	(1.50)
Tobin's Q	-0.00495***	-0.00203***	-0.00189***	-0.00495***	-0.00495***
	(-5.42)	(-19.61)	(-22.78)	(-5.41)	(-5.41)
Analyst Exp	0.01528**	0.00063	0.00087***	0.01536**	0.01536**
	(2.45)	(1.34)	(3.80)	(2.46)	(2.46)
Horizon	0.04494***	0.00027**	0.00031***	0.04494***	0.04494***
	(13.14)	(2.36)	(4.56)	(13.13)	(13.13)
Brokerage Size	-0.00432	0.00014	0.00007	-0.00435	-0.00435
	(-1.23)	(1.07)	(0.51)	(-1.23)	(-1.23)
# of Analysts	-0.10660***	-0.00143***	-0.00119***	-0.10664***	-0.10664***
	(-25.58)	(-5.71)	(-6.73)	(-25.58)	(-25.58)
Analyst Portfolio	-0.01096**	0.00036*	0.00035***	-0.01095**	-0.01095**
	(-2.58)	(1.92)	(3.27)	(-2.58)	(-2.58)
Observations	1,222,074	1,336,210	1,348,534	1,222,074	1,222,074
Adjusted R^2	0.064	0.544	0.526	0.064	0.064
Year FE	YES	YES	YES	YES	YES
Firm × Analyst FE	YES	YES	YES	YES	YES

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