Forecasting Success: How Family Social Status Shapes Analyst Performance in Financial Markets

Abstract

We examines the impact of family social status on the performance of financial analysts, emphasizing its influence on forecasting accuracy, boldness, market reactions, and career outcomes. Utilizing a dataset of 57,836 earnings forecasts from 769 analysts between 1993 and 2019, our findings reveal that analysts from affluent backgrounds demonstrate significantly higher forecast accuracy, particularly when they maintain social or educational ties with corporate executives. Additionally, these analysts are more likely to issue bold forecasts that deviate from consensus estimates, reflecting their privileged access to critical information. Market reactions further corroborate this advantage, as investors respond more favorably to upward revisions from analysts with higher family wealth. Finally, our analysis indicates that analysts from wealthy families enjoy better career trajectories, characterized by higher promotion rates and lower termination risks. This research contributes to the understanding of how family background shapes economic outcomes in the finance sector, highlighting the critical role of social capital in enhancing analytical performance.

Keywords: Financial Analysts, Forecast Accuracy, Family Social Status, Social Capital

JEL Classification: G10, G11, G14, G20, J24

1. Introduction

The economic and psychological literature extensively demonstrates the significant impact of family background on individual outcomes. Individuals born into families of higher social status tend to achieve better educational outcomes (Haveman & Wolfe, 1995; Ermisch & Francesconi, 2001), are associated with superior earnings prospects (Datcher, 1982), and are more likely to become entrepreneurs (Davidsson & Honig, 2003; Levine & Rubinstein, 2017). Building upon this body of research, we aim to examine the influence of family social status on analyst performance. This question is of substantial importance, as analysts play a critical role in the production and dissemination of financial information, with their forecasts and recommendations significantly influencing market participants' decisions. Therefore, it is essential to explore the determinants of analyst forecast accuracy and to evaluate the characteristics of the most effective analysts, as this may enhance our understanding of how family social status informs professional success in finance.

Brown et al. (2015) survey sell-side analysts and find that private communication with corporate management is the second most important determinant of forecast accuracy. Several empirical studies provide evidence that connections to corporate management enhance analysts' performance (Cohen et al., 2010; Bradley et al., 2020; Cao et al., 2020). Given that access to corporate management is a crucial factor in forecast accuracy, family social status can affect analysts' performance. The psychology literature indicates that individuals of higher social standing are often better positioned to cultivate valuable social connections through educational institutions, professional associations, and social clubs (Lin, 2000; Pichler & Wallace, 2009; Letki & Mieriņa, 2015). Furthermore, research suggests that family social status positively influences individuals' social skills (Maleki et al., 2019; Wu et al., 2020). Consequently, analysts born into affluent families may possess an advantage in establishing robust connections with corporate executives, thus gaining improved access to firm information. By leveraging their social capital, analysts from wealthy families may be expected to demonstrate higher forecast accuracy.

Conversely, the analyst profession is characterized by intense competition and self-selection. Kumar (2010) argues that female analysts face greater career barriers in this field, with only those exhibiting exceptional skills opting to become analysts. As a result, female analysts often produce more accurate earnings forecasts than their male counterparts. Similarly, individuals from less affluent families may encounter significant career barriers, which could include limited networking opportunities and fewer resources from brokerage firms. Consequently, individuals from less privileged backgrounds must possess extraordinary skills to pursue careers as analysts. Thus, analysts from less wealthy families may be associated with more accurate earnings forecasts.

Analyzing a dataset comprising 57,836 annual earnings forecasts from 769 analysts between 1993 and 2019, we find that analysts born into affluent families demonstrate superior forecast accuracy. Moreover, this relationship is particularly pronounced in forecasts where analysts and corporate executives share social networks, such as alumni associations. These findings suggest that analysts from wealthy families are adept at cultivating and leveraging strong social ties with executives of the firms they cover, thereby gaining enhanced access to firm information. This finding highlights the significant influence of family social status on the performance of financial analysts.

In our subsequent analysis, we examine the impact of family social status on analysts' forecasting behaviors, with a particular emphasis on forecast boldness. Forecast boldness refers to predictions that deviate significantly from consensus forecasts. Clement and Tse (2005) find that bold forecasts tend to incorporate more relevant private information regarding earnings. Given that analysts from wealthy families enjoy privileged access to firm executives, we anticipate that these analysts will be more inclined to issue bold forecasts. Conversely, bold forecasts inherently carry risks (Kadous et al., 2009). If analysts from less affluent families exhibit greater risk-taking tendencies, they may be more likely to issue bold earnings forecasts. Our empirical findings support our initial hypothesis, indicating that analysts from wealthy families are more likely to issue bold earnings forecasts.

In the next phase of our analysis, we explore whether market participants exhibit differential reactions to forecasts issued by analysts from affluent backgrounds compared to their counterparts. We hypothesize that if market participants perceive a potential link between analysts' family social status and the quality of their research, they will react more strongly to the information contained in revisions made by these analysts. Our empirical analyses support this conjecture, indicating that the market tends to respond more positively when analysts from wealthy backgrounds revise their forecasts upward.

Finally, we investigate the impact of family social status on analysts' career outcomes. Analysts from affluent backgrounds exhibit superior forecast accuracy, and the robust social connections they cultivate with corporate executives serve as invaluable assets for career advancement within the financial sector. Given these factors, we expect analysts from affluent backgrounds to achieve more favorable career outcomes. Our analyses provide empirical support for these expectations and show that analysts with affluent family backgrounds are more likely to be promoted and less likely to face termination in their careers.

Our paper makes several contributions to the existing literature. Firstly, it enriches the understanding of how individuals' family environments affect subsequent economic outcomes. While much of the existing literature predominantly focuses on the economic outcomes of individual households (e.g., Black et al., 2005), our work centers on security analysts, whose stock recommendations can significantly influence the decisions of financial market participants. Our research closely aligns with studies by Chuprinin and Sosyura (2018) and Du (2022). In contrast to our findings, these studies conclude that mutual fund managers and CEOs from low-income families outperform those from affluent backgrounds. However, their focus on top-level positions, where individuals from less affluent backgrounds face considerable career barriers necessitating exceptional skills for advancement, complicates direct comparisons. The precise influence of family social status on lower-level employees remains largely unexamined. By focusing on security analysts, our research provides valuable insights into how family social status affects individuals' career trajectories.

Secondly, our paper contributes to the literature on the influence of analysts' characteristics on performance (e.g., Kumar, 2010; Cao et al., 2020; Frijns & Garel, 2021). Our findings suggest that analysts' family social standing is a significant determinant of forecast accuracy, extending the existing body of literature, which has traditionally emphasized factors such as educational background, experience, and gender in evaluating analysts' performance. By highlighting the role of family wealth and social capital, we introduce a novel dimension to understanding analyst effectiveness. This insight not only enriches the theoretical framework surrounding analyst performance but also underscores the importance of considering social dynamics when assessing forecasting accuracy. Furthermore, our results suggest that the implications of family background extend beyond individual performance to influence broader market reactions and career trajectories, inviting further exploration into how social factors shape professional outcomes in finance.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive literature review that contextualizes our study within existing research on social capital and analyst performance, highlighting key theories and findings. Section 3 details the hypothesis development, outlining the theoretical framework that supports our examination into the relationship between family social status and forecasting accuracy. In Section 4, we describe our data sources and empirical methodology, offering insights into our analytical approach and the dataset used for our analyses. Section 5 presents the empirical results, showing the key findings of our study and their implications for understanding the influence of family background on analyst performance. Finally, Section 6 concludes the paper, summarizing the main findings and discussing the broader implications of our research for the finance industry and future studies on the role of social capital in professional settings.

2. Literature Review

Social capital is generally defined as the valuable resources accessible to individuals or groups through their social relationships (Portes and Sensenbrenner, 1993; Portes, 1998). Its significance in influencing individuals' lives and career trajectories has long been recognized. For example, Burton et al. (2012) demonstrate that patients with higher levels of social capital are more likely to receive health-related advice via social media. Moreover, individuals with greater social capital tend to embark on entrepreneurial ventures, with these entrepreneurs reporting higher rates of initial sales and profitability (Davidsson and Honig, 2003). Research has also shown that employees possessing substantial social capital experience improved career outcomes, including increased salaries and promotion rates (Burt, 1992; Seibert, Kraimer, and Liden, 2001).

At the firm level, Engelberg et al. (2012) demonstrate that companies benefit from lower interest rates when their management teams are connected to banks. Similarly, Das and Teng (2002) highlight that social capital fosters trust and reduces transaction costs, enhancing firms' access to financial resources. Additionally, Sorensen and Stuart (2001) find that firms with strong social networks are more successful in securing financing, leading to improved performance outcomes. Shao and Sun (2021) illustrate how entrepreneurs leverage social capital to secure venture capital funding.

The concept of social capital significantly affects investment practices and outcomes. Granovetter (1973) highlights the importance of weak ties within social networks, suggesting that these connections facilitate the flow of information and opportunities vital for investors. Cohen et al. (2008) demonstrate that mutual fund managers with ties to corporate management achieve superior investment returns, underscoring the role of social connections in investment performance. Furthermore, Hong et al. (2005) find that individual fund managers with extensive social networks are more likely to receive valuable information, which enhances their investment decision-making.

The impact of social capital extends to the performance of sell-side analysts, who rely on social connections to enhance their access to corporate information, thereby improving their forecasting accuracy. Brown et al. (2015) note that analysts with robust ties to corporate management benefit from access to privileged information, resulting in more accurate earnings forecasts. Cohen et al. (2010) also show that educational connections between analysts and management yield more favorable buy recommendations, underscoring the significance of personal relationships in the financial sector. Similarly, Bradley et al. (2020) demonstrate that analysts with professional connections to coverage firms tend to produce more accurate earnings forecasts and offer more informative buy and sell recommendations. Additionally, analysts perceived as attractive are able to garner more information from executives, which contributes to their performance (Cao et al., 2020).

In summary, the literature consistently illustrates that social capital is a vital asset within the finance industry, influencing both investment decisions and the effectiveness of analysts' forecasts.

3. Hypothesis Development

While analysts benefit from their social networks, the extent of these benefits can differ significantly among individuals. Fang and Huang (2017) reveal that male analysts tend to derive greater advantages from their social connections with corporate management compared to their female counterparts, leading to improved forecast accuracy. This disparity suggests that factors such as family social status may influence an analyst's ability to cultivate and leverage these critical social connections.

This argument is bolstered by established findings in the psychological literature that highlight the correlation between social status and the strength of social networks. Individuals of higher social status typically maintain larger networks, enabling them to capitalize on these connections more effectively (Lin, 2001; Pichler and Wallace, 2009; Letki and Mieriņa, 2015). Consequently, analysts with elevated social status are more likely to have access to influential corporate executives, enhancing their informational advantage. Moreover, the concept of "homophily" underscores the tendency for social connections to form among individuals with similar socio-economic backgrounds (McPherson et al., 2001; Kossinets and Watts, 2009). Higher-status analysts are thus positioned to connect more readily with other high-status individuals, including corporate managers, which can further amplify their informational resources.

Additionally, individuals from affluent backgrounds often exhibit superior social skills and networking abilities, attributes that are typically nurtured through early exposure to diverse social environments (Lin, 2001). These enhanced interpersonal skills facilitate the establishment of robust professional relationships, further supporting the notion that social capital is intertwined with family social status. In this context, we propose that analysts hailing from wealthier families are better equipped to access critical corporate information, ultimately leading to more accurate earnings forecasts. Based on this rationale, we formulate our hypothesis as follows:

H1: Analysts from affluent families are associated with improved forecast accuracy.

Furthermore, we anticipate that the interaction between analysts' family social status and their professional connections may create synergies that enhance their analytical capabilities. Previous research has indicated that the quality of relationships analysts maintain with corporate executives directly impacts their ability to generate reliable forecasts (Brown et al., 2015; Cohen et al., 2010). While analysts from affluent backgrounds are more likely to possess advantageous networks, the extent to which these advantages translate into forecast accuracy is significantly influenced by their educational ties to corporate executives. Analysts with higher family social status often have access to prestigious educational institutions, which can facilitate connections with influential industry figures. The quality of these educational connections can enhance trust and facilitate the exchange of critical information, thereby improving analysts' forecasting abilities. Studies indicate that educational ties can lead to more favorable interactions between analysts and management, as these relationships often carry a sense of familiarity and shared background, fostering open communication (Cohen et al., 2010).

The significance of educational connections extends beyond immediate informational benefits. Analysts who leverage their educational backgrounds to connect with corporate executives may also enhance their professional reputation and credibility, leading to increased access to non-public insights. This dynamic suggests that the interplay between family social status and educational connections creates a synergistic effect, amplifying the analyst's capacity to generate accurate forecasts.

Therefore, we hypothesize that:

H2: The positive relationship between analysts' family social status and forecast accuracy is moderated by the strength of their educational connections with corporate management.

These hypotheses collectively underscore the significance of social capital and family background in shaping the forecasting abilities of analysts within the finance industry.

4. Data

4.1. Analyst Forecast Data

The annual forecast data for analysts is from the I/B/E/S database. We retain only those analysts who have provided at least one annual earnings forecast with a horizon ranging from one to twelve months during the period from 1993 to 2019. In instances where an analyst has issued multiple forecasts for a given firm within a single year, we select the most recent forecast for inclusion in our dataset. Given that the I/B/E/S file lists analysts by their last names and initials of their first names, we follow the methodology outlined by Gibbons et al. (2021) to match the forecast data from I/B/E/S with corresponding records from Bloomberg. This process facilitates the acquisition fo the full names of the analysts.

Subsequently, we conduct a manual search for the LinkedIn profiles of these analysts using their full names and current employers. This process leads us to identify 496 analysts who publicly disclose their high school affiliations on their LinkedIn profiles. For the remaining analysts, we perform manual searches on Classmates.com, which is recognized as the largest high school dataset recently utilized in financial research (Duchin et al., 2021). To further enhance the accuracy of our matches, we compare the facial images of analysts from their LinkedIn profiles with those found in their respective high school yearbooks. This thorough procedure allows us to identify an additional 273 analysts and their corresponding high school affiliations. Ultimately, our final sample comprises 769 analysts who collectively provide a total of 57,836 annual forecasts, providing a robust dataset for our analysis.

4.2. Variables

4.2.1. Analyst forecast accuracy

Following Clement (1999), we measure analyst performance using relative forecast errors (*RFE*). More specifically, *RFE* is defined as follows:

$$RFE_{i,j,t} = \frac{AFE_{i,j,t} - MAFE_{j,t}}{MAFE_{j,t}}, \tag{1}$$

where $AFE_{i,j,t} = |Forecast\ EPS_{i,j,t} - Actual\ EPS_{i,j,t}|$. Here, i, j, and t denote the individual analyst, the firm, and the year, respectively, while $MAFE_{j,t}$ represents the mean absolute forecast error for firm j and year t. A lower of RFE indicates a more accurate forecast.

4.2.2. Family wealth

We estimate analysts' family wealth during their formative years by examining the median household income in the neighborhoods where their high schools are situated. The median household income data is from the U.S. Census of Population and Housing, as reported by the U.S. Census Bureau at the census-tract level every decade. In line with the approach taken by Du (2022), we align each analyst's high school location with the corresponding census tract from the most relevant U.S. census file. For instance, analysts who graduated from high schools between 1966 and 1975 are matched with the 1970 U.S. census data to obtain pertinent information on neighborhood income. This methodology allows us to accurately reflect the socio-economic context in which the analysts were raised, thereby providing a more comprehensive understanding of the potential impact of family wealth on their professional advancement.

Furthermore, analyzing median household income at the neighborhood level enables us to capture the broader socio-economic environment influencing these analysts during their careers. The economic resources available to families can significantly shape children's educational opportunities, social networks, and overall aspirations. By linking analysts to specific income data, we can explore how varying levels of family wealth might correlate with their subsequent career choices and performance outcomes. This approach highlights the importance of socio-economic factors in shaping professional success and offers insights into the potential disparities in access to opportunities within the finance industry.

5. Methodology

To investigate the influence of analysts' family wealth on performance, we conduct the following OLS regression:

$$RFE_{i,j,t} = \alpha + Ln(Family\ Wealth)_i + Controls + Year\ FE + \varepsilon_{i,j,t}, \tag{2}$$

where $RFE_{i,j,t}$ represents the relative forecast error associated with analyst i's forecast for firm j in year t. *Ln(Family Wealth)* denotes the natural logarithm of the family wealth of the analysts. We incorporate a range of control variables to account for factors that may influence the accuracy of analysts' forecasts.

Among the control variables, *Gender* captures the gender of the analyst, assigning a value of 1 to female analysts and 0 to male analysts. This binary coding enables us to assess the potential impact of gender on forecasting performance. Previous research indicates that analysts who have social connections with the executives of the firms they cover tend to produce more accurate forecasts (Jang & Huang, 2017). *Connect* measures whether an analyst shares an educational affiliation with the executives of the firms under consideration. Additionally, *General Experience* and *Firm Experience* quantify the number of years the analyst has worked in the profession and the number of years they have been following a particular firm, respectively. *Portfolio Size* reflects the total number of firms an analyst covers in a given year, which serves to control for the influence of analysts' diligence and workload on forecasting accuracy. To address potential discrepancies arising from the analysts' brokerage firms, *Top10* indicates whether the analyst's firm ranks within the top ten percentile of brokerage firms. Lastly, *Horizon* accounts for the number of days between the forecast and the earnings announcement date, as shorter forecasting horizons typically allow analysts to utilize more current information, thereby enhancing forecast accuracy.

Detailed descriptions of these control variables can be found in Appendix A. For the purpose of robust statistical analysis, we apply winsorization to all continuous variables at the 1^{st} and 99^{th} percentiles to mitigate the influence of outliers. Furthermore, we incorporate year fixed effects and cluster standard errors at both the analyst and firm levels to ensure the reliability of our estimations. This comprehensive approach allows us to rigorously assess the relationship between analysts' family wealth and their forecasting performance while controlling for various determinants.

6. Empirical Results

6.1. Summary Statistics

The summary statistics presented in Table 1 provide a comprehensive overview of both the dependent and independent variables used in this study. *RFE* has a mean of -0.074 and a standard deviation of 0.856. The interquartile range (IQR) is substantial, with the 25th percentile at -0.625 and the 75th percentile at 0.149, indicating a wide dispersion in forecast accuracy among analysts. The average family wealth, expressed in 1950 dollars, stands at $5,517 thousand, with a standard deviation of $2,201. The data suggest that family wealth is positively skewed, as indicated by the median of $6,125 and the IQR ranging from $4,655 to $6,989.

[Insert Table 1 Here]

The *Gender* variable shows a mean of 0.071, indicating that only 7.1% of analysts in the sample are female. This highlights a significant gender disparity in the field of analysis. The *Connect* variable reveals that 14.5% of analysts have educational ties with executives of their coverage firms. The mean of *Ln(Family Wealth)* is 8.478 (SD = 0.611), with a relatively narrow range in the interquartile distribution, suggesting a more uniformity in the log-transformed data compared to raw family wealth. General experience averages 9.116 years (SD = 8.512), while firm-specific experience averages 3.102 years (SD = 3.781). The significant variation in general experience suggests a diverse cohort of analysts in terms of career length. Analysts cover an average of 16.238 firms (SD = 7.924), reflecting a considerable workload and the potential for varied forecasting experiences. Approximately 58.7% of analysts work for top brokerage houses, indicating a notable concentration of analysts within high-ranking firms. The average forecast horizon is 122.04 days (SD = 74.239), with a median of 100 days, suggesting a typical forecasting period that allows analysts to incorporate recent information effectively.

[Insert Table 2 Here]

Table 2 displays the correlation matrix, providing important insights into the relationships between the relative forecast error (*RFE*) and various independent and control variables. The coefficients are statistically significant at different levels, with asterisks indicating their significance.

Overall, the correlation matrix highlights several noteworthy relationships. While some variables show minimal associations with *RFE*, the correlation coefficient of -0.024 between *RFE* and the natural logarithm of family wealth indicates a statistically significant negative relationship, suggesting that analysts from wealthier families tend to have lower forecast errors. Furthermore, the strong correlation between forecast horizon and forecast error emphasizes the critical role of timely information in improving forecast accuracy.

Additionally, the correlation between the main independent variable, the natural logarithm of family wealth, and other control variables remains low, with the highest pairwise correlation at 0.163, which helps to mitigate concerns about multicollinearity.

6.2. Main Results

Table 3 presents the results of regression analyses examining the relationship between various independent variables and the relative forecast error (*RFE*). Three models are estimated, with Model (1) focusing primarily on the impact of family wealth, while Models (2) and (3) incorporate additional control variables.

[Insert Table 3 Here]

In Model (1), the coefficient for the natural logarithm of family wealth is -0.035, statistically significant at the 5% level. This indicates that an increase in family wealth is associated with a decrease in *RFE*, suggesting that analysts from wealthier families tend to produce more accurate forecasts. In Model (2), the coefficient is -0.038 and is statistically significant at the 1% level, indicating that the introduction of additional variables does not substantially alter this relationship. Model (3) introduces the variable "*High Family Wealth*," which takes a value of 1 if an analyst's family wealth is above the sample median and 0 otherwise. This variable has a coefficient of -0.039, and also significant at 1% level. Collectively, these findings indicate that analysts from affluent backgrounds demonstrate better forecast accuracy. In the economic term, Model (3) suggests that forecasts of analysts from wealthy families are associated with approximately 3.9% more accurate than those of their peers. For comparison, Bradley et al. (2017) find that analysts making forecasts in industries related to their prior experience are 3.58% more accurate than those in unrelated industries, highlighting the economically significant effect of family wealth on performance.

The R-squared values are 0.93% for Model (1) and increase to 11.74% for Models (2) and (3), indicating that the inclusion of additional control variables enhances the models' explanatory power and captures a greater proportion of the variability in forecast errors.

Regarding of control variables, we find that analysts exhibit superial forecast accuracy in firms which they share social connections with executives or directors of the coverage firms.

Likewise, analysts who affiliated with major brokerage firms are associated with greater forecasting precision. Conversely, forecast errors increase with longer forecast horizons. These results are consistent with previous literature (e.g. Bradley et al., 2020; Cao et al., 2020).

6.3. Channels

In this section, we explore the mechanisms by which family social status influences analyst performance. Social connections, such as alumni ties, can grant analysts access to valuable information about firms (Cohen et al., 2010). However, the extent to which analysts can leverage their social capital varies significantly (Fang & Huang, 2017). We posit that if family social status enables analysts to effectively utilize their social connections, the impact of this status on forecast accuracy should be particularly pronounced in firms where analysts and management share alumni networks.

[Insert Table 4 Here]

To assess this hypothesis, we first examine whether analysts from affluent backgrounds exhibit a greater tendency to cover firms with which they have social connections to executives. We contend that if analysts from wealthy families benefit from their social networks, they should demonstrate a higher likelihood of covering connected firms. Panel A of Table 4 presents our findings, indicating that analysts from low-income families cover 13.04% of connected firms, while those from high-income families cover 15.97%. This difference is statistically significant at the 1% level, suggesting that analysts from wealthier backgrounds are more inclined to follow firms with which they share connections, thus providing initial support for our hypothesis.

Next, we examine whether analysts with affluent backgrounds generate more accurate forecasts for firms with which they share social connections to executives. To this end, we modify Equation (2) to include an interaction term between *Ln(Family Wealth)* and *Connect*.

In Panel B of Table 4, the coefficient on the interaction term *Ln(Family wealth)×Connect* is negative and significant at the 1% level, suggesting that analysts from wealthy families significantly benefit from their social connections with executives, leading to improved forecast accuracy.

Overall, the results in Table 4 underscore the critical role of social status in leveraging social capital. Analysts from affluent backgrounds are better positioned to utilize their connections to enhance their professional performance, particularly in terms of forecast accuracy.

6.4. Endogeneity

In our primary analyses, we assess analysts' family wealth based on their childhood residence locations. However, individual characteristics can vary significantly across different geographical regions (Berry et al., 2014). If an analyst's childhood location is correlated with latent traits that influence performance, the earlier results may be biased. To address this concern rigorously, we employ an instrumental variable approach.

Following the methodology outlined by Du (2022), we utilize per capita economic loss due to natural disasters in the county where an analyst resided during their formative years as an instrument for family wealth. This instrument is appropriate because per capita economic damage in a county is negatively correlated with estimated family wealth, which we approximate using median household income in the neighborhood. Importantly, we find no discernible correlation between analysts' skills and their exposure to natural disasters, thus supporting the validity of our instrument. [1]

[1] Bernile et al., (2017) find that CEOs' natural disaster experience significantly impact their risk-taking behavior. However, the litelature provides no evidence of the influence of natural disaster experiences on performance.

Data on economic losses caused by natural disasters are obtained from the National Oceanic and Atmospheric Administration (NOAA), encompassing crop damages and property damages at the county level from 1950 to 2010. We match this data with the U.S. Census of Population and Housing, from which we derive median household income. For instance, the median household income from 1970 is aligned with disaster events occurring between 1961 and 1970.

Table 5 presents the results from our two-stage least squares (2SLS) estimation. In the first stage, we observe a significant negative correlation between economic loss and analysts' family wealth, with a coefficient of -0.083. This finding indicates that greater economic losses in an analyst's childhood county are associated with lower family wealth, thus validating our instrumental variable. The F-statistic confirms the strength of this instrument, demonstrating its appropriateness for further analysis.

[Insert Table 5 Here]

In the second stage, we analyze the impact of estimated family wealth on forecast accuracy. The results show that $Ln(\widehat{Family\,Wealth})$ has a coefficient of -0.126, statistically significant at the 1% level (p = 0.002). This suggests that analysts who come from wealthier families, as estimated through our instrument, exhibit improved forecast accuracy. The inclusion of control variables and fixed effects for year and analyst-firm clusters enhances the robustness of our findings.

Overall, the results in Table 5 reinforce the causal relationship between analysts' family social status and forecast accuracy, underscoring the importance of socioeconomic factors in evaluating forecasting performance. The R-squared values indicate that our models explain a significant proportion of the variability in the data, with 18.11% in the first stage and 11.14% in the second stage.

6.5. Additional Tests

6.5.1. Analysts' family social status and forecast boldness

In this section, we explore the impact of analysts' family wealth on their forecast boldness. Prior literature indicates that access to private information significantly affects analysts' forecast boldness (Clement, 1999). We hypothesize that analysts from affluent families, who are likely to have superior access to corporate management and insider information, are more inclined to issue bold forecasts. This privileged access may embolden them to deviate from consensus estimates, resulting in forecasts that demonstrate a pronounced deviation.

Conversely, it is also conceivable that analysts from low-income families may exhibit higher levels of risk tolerance, which could lead them to issue bolder earnings forecasts. This behavior may stem from a desire to distinguish themselves in a competitive field, where bold forecasts attract greater attention and provide a pathway to career advancement. Additionally, analysts from less affluent backgrounds might possess a different risk assessment framework, shaped by their personal experiences and socioeconomic status, prompting them to take greater professional risks.

Following Clement (2005), we create a variable termed "*Bold*," which is coded as 1 if an earnings forecast exceeds both the prevailing consensus and the analyst's most recent forecast. We then estimate the following logit model:

$$Bold_{i,j,t} = \alpha + \ Ln(Family\ Wealth)_i + Controls + Year\ FE + \ \varepsilon_{i,j,t}, \tag{3}$$

where i, j, and t denote the individual analyst, the firm, and the year, respectively.

Table 6 presents the results of the logit regression analysis. In Column 1, the coefficient for *Ln(Family Wealth)* is positive and statistically significant, indicating that analysts from affluent families are more likely to issue bold forecasts. Notably, Columns 2 and 3 further decompose bold forecasts into bold-positive and bold-negative forecasts, respectively. The results show that analysts from wealthy backgrounds are significantly more inclined to issue bold-positive forecasts (coefficient = 0.098, p-value = 0.000) while being less likely to issue bold-negative forecasts (coefficient = -0.061, p-value = 0.001).

[Insert Table 6 Here]

These findings align with the work of Cohen, Frazzini, and Malloy (2010), which suggests that social connections to management, particularly through shared alumni networks, provide mutual fund managers with insights into positive earnings potential. The results bolster the argument that analysts from wealthier families benefit from enhanced access to firm-specific information, thereby influencing their forecasting behavior. Since bold forecasts are often correlated with the integration of private information, our findings imply that family social status enables analysts to cultivate social capital, significantly impacting their behaviors and performance within financial markets.

6.5.2. Market reactions

In the preceding sections, we find that analysts from affluent families demonstrate superior forecast accuracy. We now explore whether market participants recognize this connection. We obtain the revision dates from the I/B/E/S database and calculate the cumulative abnormal returns (CARs) over a window of [-1, +1] days centered around each forecast announcement date. We then employ the following regression model:

$$CAR_{i,j,t} = \alpha + \ Ln(Family\ Wealth)_i + Controls + Year\ FE + \ \varepsilon_{i,j,t}, \tag{4}$$

where i, j, and t denote the individual analyst, the firm, and the year, respectively.

The results from our analysis, presented in Table 7, provide valuable insights. In Column 1, which examines upward revisions, the coefficient for *Ln(Family Wealth)* is positive and statistically significant, indicating that the market reacts more favorably to upward revisions made by analysts from wealthier backgrounds. This suggests that investors perceive these analysts to produce higher-quality upward revisions. In contrast, Column 2 shows the market reaction to downward revisions. Here, the coefficient for *Ln(Family Wealth)* is negative but not statistically significant (p-value = 0.432). This indicates that downward revisions do not elicit a strong market response.

[Insert Table 7 Here]

Furthermore, the coefficient for the variable *Connect* is positive and marginally significant for upward revisions (coefficient = 0.072, p-value = 0.041), suggesting that analysts with connections to corporate management also influence market reactions positively when issuing upward revisions. However, the negative coefficient for *Connect* in downward revisions (coefficient = -0.039, p-value = 0.135) indicates that such connections do not mitigate the negative market response associated with downward revisions.

Overall, these findings reinforce the notion that analysts from wealthy families not only produce more accurate forecasts but also generate more significant market reactions, particularly for positive revisions. These results suggest that family wealth facilitates access to privileged positive information, which in turn influences both forecast behaviors and the corresponding market dynamics.

6.5.3. Career outcomes

In this section, we investigate the influence of analysts' family wealth on their career outcomes, specifically focusing on promotion, demotion, and termination. Prior research indicates that access to corporate management is a critical determinant of analysts' career trajectories (Jiang et al., 2016). To assess this, we construct three measures of career outcomes: promotion, demotion, and termination. An analyst is considered promoted if they move to a larger brokerage firm in the following year, demoted if they move to a smaller one, and terminated if they cease to appear in the I/B/E/S database. We estimate the following logit model to examine these outcomes:

$$Outcome_{i,t} = \alpha + \ Ln(Family\ Wealth)_i + Controls + Year\ FE + \ \varepsilon_{i,j,t}, \qquad (5)$$

where *Outcome* indicates three career outcomes (promote, demote, or termination), and i, j, and t denote the individual analyst, the firm, and the year, respectively.

The results presented in Table 8 provide valuable insights into how family social status influences analysts' career outcomes. The coefficient for *Ln(Family Wealth)* in the promotion model is positive and statistically significant (0.159, p-value = 0.035), indicating that analysts from affluent backgrounds are more likely to be promoted. This suggests that the resources and connections associated with higher family wealth may facilitate upward mobility within the industry.

In addition, the coefficient for *Ln(Family Wealth)* in the termination model is negative and highly significant (coefficient = -0.255, p-value = 0.000). This finding indicates that analysts from wealthier families are less likely to experience termination, reinforcing the notion that social capital derived from family wealth contributes to job security in this profession.

Interestingly, the coefficient for demotion is not statistically significant (coefficient = -0.088, p-value = 0.438), suggesting that family wealth may have a more pronounced effect on promotion and termination than on demotion. This could imply that while affluent analysts may benefit from more opportunities for advancement and reduced risk of job loss, the factors influencing demotion may be more complex or less directly related to family wealth.

Overall, these findings underscore the significant role of family wealth in shaping analysts' career trajectories, highlighting the advantages that come from social status in the financial industry. As analysts with affluent backgrounds appear to enjoy both enhanced promotional prospects and greater job security.

7. Conclusion

This study examines the intricate relationships between analysts' family wealth, social capital, and their forecasting accuracy, contributing to a growing body of literature on the influence of social status within the finance sector. Our empirical analyses reveal compelling evidence supporting the hypothesis that analysts from affluent families tend to produce more accurate earnings forecasts. The results indicate that family wealth not only enhances analysts' access to privileged information but also serves as a crucial determinant of their overall forecasting performance.

The findings demonstrate that analysts with higher family wealth are associated with lower relative forecast errors (*RFE*), suggesting a pronounced advantage in accuracy due to their enhanced social connections and informational resources. Specifically, analysts hailing from wealthier backgrounds are more likely to receive crucial insights from corporate executives, facilitated by their social networks, which are often larger and more influential. This aligns with previous literature that underscores the role of social capital in shaping financial decision-making and investment outcomes (Cohen et al., 2008; Brown et al., 2015).

Moreover, the study extends the discourse on social capital by examining the interplay between family wealth and educational connections. The results reveal that analysts with robust educational ties to corporate management experience an amplification of the benefits derived from their family background. This interaction emphasizes the importance of both family social status and the quality of educational networks in enhancing analysts' forecasting abilities. In essence, while family wealth provides a foundation for accessing valuable information, the strength of educational connections further enables analysts to leverage this information effectively, resulting in improved forecasting accuracy.

Our findings also highlight significant disparities in the financial industry, particularly regarding social capital and gender. The limited connections among analysts underscore the necessity for fostering social networks that can enhance access to vital corporate information.

In addition, the underrepresentation of female analysts suggests potential barriers to access and success within the field, echoing earlier research on the gendered dimensions of social capital (Fang and Huang, 2017).

In summary, this study reinforces the notion that social capital is a vital asset in the finance industry, influencing both investment decisions and the effectiveness of analysts' forecasts. By elucidating the impact of family wealth and educational connections, we contribute to a nuanced understanding of the factors that shape analysts' performance in financial markets. Future research should continue to investigate these dynamics, exploring how social capital can be cultivated to enhance forecasting accuracy and career outcomes in an increasingly competitive financial landscape.

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Table 1. Summary Statistics

The table presents summary statistics for variables used in the studies. All variables are defined in Appendix A.

Variable	N	Mean	SD	P25	P50	P75
Dependent Var.						
RFE	57,836	-0.074	0.856	-0.625	-0.244	0.149
Bold	43,885	0.757	0.429	1	1	1
Bold-Positive	43,885	0.379	0.485	0	0	1
Bold-Negative	43,885	0.377	0.484	0	0	1
$CAR[-1,1]_{\text{upward revision}}$	81,343	1.639	12.446	-5.002	1.392	8.015
$CAR[-1,1]_{\text{downward revision}}$	65,129	-2.231	8.068	-5.318	-1.198	1.844
Promote	6,717	0.095	0.293	0	0	0
Demote	6,717	0.091	0.287	0	0	0
Terminate	6,717	0.114	0.318	0	0	0
Independent Var.						
Family wealth ($thousand)	57,836	5.517	2.201	4.655	6.125	6.989
Ln(Family Wealth)	57,836	8.478	0.611	8.446	8.721	8.852
Control Var.						
Female	57,836	0.071	0.256	0	0	0
Connect	57,836	0.145	0.352	0	0	0
General Experience	57,836	9.116	8.512	2	8	15
Firm Experience	57,836	3.102	3.781	0	2	4
Portfolio Size	57,836	16.238	7.924	11	15	20
Top 10	57,836	0.587	0.492	0	1	1
Forecast Horizon	57,836	122.04	74.239	88	100	123

Table 2. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RFE (1)	1								
Ln(Family Wealth) (2)	-0.024***	1							
Female (3)	0.015***	-0.010**	1						
Connect (4)	-0.014***	0.032***	-0.006	1					
Ln(General Experience) (5)	-0.011***	0.163***	-0.074***	0.053***	1				
Ln(Firm Experience) (6)	-0.006	0.039***	-0.017***	0.096***	0.419***	1			
Ln(Portfolio Size) (7)	0.004	0.019	-0.089***	-0.015***	0.325***	0.201***	1		
Top 10 (8)	-0.014***	-0.014***	0.047***	-0.001	0.032***	0.043***	0.139***	1	
Ln(Forecast Horizon) (9)	0.339***	0.018*	0.012***	0.047***	0.001	0.005	-0.059***	-0.004	1

The symbols *, **, and *** are used to indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. The Effect of Analysts' Family Wealth on Analyst Forecast Errors

The table presents the results of an Ordinary Least Squares (OLS) regression analysis examining the impact of analysts' family wealth on analyst forecast errors. P-values are provided in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Dependent Var.	RFE	RFE	RFE
Model	(1)	(2)	(3)
Ln(Family Wealth)	-0.035**	-0.038***	
	[0.031]	[0.009]	
High Family Wealth			-0.039***
			[0.008]
Connect		-0.012***	-0.013***
		[0.002]	[0.001]
Female		0.031	0.030
		[0.229]	[0.259]
Ln(General Experience)		-0.001	-0.002
		[0.977]	[0.816]
Ln(Firm Experience)		-0.006	-0.006
		[0.355]	[0.387]
Ln(Portfolio Size)		0.004	0.004
		[0.419]	[0.417]
Top 10		-0.018*	-0.015
		[0.203]	[0.291]
Ln(Forecast Horizon)		0.544***	0.544***
		[0.000]	[0.000]
Year FE	Yes	Yes	Yes
Analyst-Firm Cluster	Yes	Yes	Yes
N	57,836	57,836	57,836
R^2	0.93%	11.74%	11.72%

Table 4. The Effect of Analysts' Family Wealth and Connection on Analyst Forecast Errors

Panel A reports statistics on analyst connections based on analysts' family wealth. Panel B presents the results of an Ordinary Least Squares (OLS) regression analysis examining the impact of analysts' family wealth and connection on analyst forecast errors. P-values are provided in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A. Number of Connections by Analysts' Family Wealth

	High Family Wealth	Low Family Wealth	Diff	p-value
Connect	15.97%	13.04%	2.93%***	0.000
N	28,895	28,851		

Panel B. The Effect of Analysts' Family Wealth and Connection on Analyst Forecast Errors

Dependent Var.	RFE	RFE
Ln(Family Wealth)	-0.033**	
	[0.012]	
Ln(Family Wealth) × Connect	-0.015***	
	[0.008]	
High Family Wealth		-0.034**
		[0.017]
High Family Wealth × Connect		-0.017**
		[0.025]
Connect	0.121	-0.006
	[0.268]	[0.420]
Female	0.032	0.029
	[0.222]	[0.251]
Ln(General Experience)	-0.001	-0.002
	[0.961]	[0.806]
Ln(Firm Experience)	-0.006	-0.006
	[0.361]	[0.381]
Ln(Portfolio Size)	0.004	0.004
	[0.419]	[0.417]
Top 10	-0.017	-0.015
	[0.217]	[0.301]
Ln(Forecast Horizon)	0.544***	0.544***
	[0.000]	[0.000]
Year FE	Yes	Yes
Analyst-Firm Cluster	Yes	Yes
N	57,836	57,836
R^2	11.73%	11.72%

Table 5. 2SLS - Instrumental Variable Approach Using Economic Loss

The table presents the results of an 2SLS regression analysis examining the impact of analysts' family wealth on analyst forecast errors. P-values are provided in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Dependent Var.	Ln(Family Wealth)	RFE
Model	(1)	(2)
Economic Loss	-0.083***	
	[0.000]	
$\mathrm{Ln}(\widehat{\mathrm{Family\ Wealth}})$		-0.126***
		[0.002]
Controls	Yes	Yes
Year FE	Yes	Yes
Analyst-Firm Cluster	Yes	Yes
F-statistic (p-value)	0.000	
N	55,354	55,354
R^2	18.11%	11.14%

Table 6. Bold Forecasts

The table presents the results of a probit regression analysis examining the impact of analysts' family wealth on analyst forecast boldness. P-values are provided in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Logit		
Dependent Var.	Bold	Bold Positive	Bold Negative
Model	(4)	(5)	(6)
Ln(Family Wealth)	0.045**	0.098***	-0.061***
	[0.017]	[0.000]	[0.001]
Connect	0.021*	0.042***	-0.029***
	[0.082]	[0.000]	[0.009]
Female	0.091	0.001	0.073
	[0.311]	[0.976]	[0.371]
Ln(General Experience)	0.009	0.024	-0.016
	[0.557]	[0.141]	[0.309]
Ln(Firm Experience)	-0.002	-0.039**	0.038**
	[0.897]	[0.024]	[0.024]
Ln(Portfolio Size)	-0.084***	-0.005	-0.072***
	[0.000]	[0.843]	[0.006]
Top 10	-0.055**	0.018	-0.061***
	[0.032]	[0.429]	[0.005]
Ln(Forecast Horizon)	0.227***	0.265***	-0.079***
	[0.000]	[0.000]	[0.001]
Lag_RFE	-0.108***	-0.093***	0.002
	[0.000]	[0.000]	[0.886]
Year FE	Yes	Yes	Yes
Analyst Cluster	Yes	Yes	Yes
Firm Cluster	Yes	Yes	Yes
N	43,885	43,885	43,885
R^2 or Pseudo R^2	1.31%	1.60%	1.48%

Table 7. Market Reaction

The table presents the results of an logit regression analysis examining the impact of analysts' family wealth on the market reaction to analyst forecast revision. P-values are provided in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	Upward Revision	**Downward Revision**
Dependent Var.	CAR[-1,1]	CAR[-1,1]
Model	(1)	(2)
Ln(Family Wealth)	0.181**	-0.047
	[0.036]	[0.432]
Connect	0.072**	-0.039
	[0.041]	[0.135]
Female	0.338	-0.106
	[0.309]	[0.619]
Ln(General Experience)	0.098	-0.087
	[0.305]	[0.185]
Ln(Firm Experience)	0.009	-0.016
	[0.925]	[0.845]
Portfolio Size	-0.181	-0.249**
	[0.256]	[0.017]
Top 10	0.195*	-0.017
	[0.091]	[0.828]
Forecast Horizon	0.013	0.033
	[0.908]	[0.68]
Lag_RFE	-0.089	0.079
	[0.214]	[0.130]
Year FE	Yes	Yes
Analyst-Firm Cluster	Yes	Yes
N	81,343	65,129
R^2	7.70%	7.97%

Table 8. The Effect of Analysts' Family Wealth on Career Outcomes

The table presents the results of a logit regression analysis examining the impact of analysts' familial wealth on career outcomes. P-values are indicated in parentheses, with *, **, and *** representing statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Var.	Promote	Demote	Termination
Model	(1)	(2)	(3)
Ln(Family Wealth)	0.159**	-0.088	-0.255***
	[0.035]	[0.438]	[0.000]
Average Connect	0.034**	-0.036	-0.118**
	[0.049]	[0.301]	[0.041]
Female	-0.257**	0.034	0.083
	[0.025]	[0.734]	[0.573]
Ln(General Experience)	0.097***	0.039	-0.029
	[0.000]	[0.156]	[0.663]
Average Firm Experience	0.129***	-0.072**	0.443***
	[0.000]	[0.015]	[0.000]
Portfolio Size	-0.284***	-0.114***	-0.042***
	[0.000]	[0.007]	[0.000]
Top10	-0.605***	0.266***	-0.281*
	[0.000]	[0.002]	[0.066]
Average Forecast Horizon	0.111*	0.243***	0.292***
	[0.064]	[0.000]	[0.000]
Average RFE	-0.055	0.044	0.073
	[0.175]	[0.271]	[0.324]
Analyst Cluster	Yes	Yes	Yes
N	6,717	6,717	6,717
Pseudo R2	3.64%	1.95%	19.03%

Appendix A

Variables	Definition	Sources
RFE	Absolute forecast error for analyst i's forecast of firm j for year t, minus mean absolute forecast error for firm j for year, scaled by mean absolute forecast error for firm j for year t.	IBES
Bold	Bold forecast takes the value of one when a forecast is either above or below both the prevailing consensus and an analyst's own most recent forecast.	IBES
Bold-Positive	Bold-positive forecast takes the value of one when a forecast is above both the prevailing consensus and an analyst's own most recent forecast.	IBES
Bold-Negative	Bold-negative forecast takes the value of one when a forecast is below both the prevailing consensus and an analyst's own most recent forecast.	IBES
CAR[-1,1]upward revision	Cumulative abnormal return (CAR) from day -1 to day +1 around the analyst's upward revision date.	IBES, CRSP
CAR[-1,1]downward revision	Cumulative abnormal return (CAR) from day -1 to day +1 around the analyst's downward revision date.	IBES, CRSP
Promote	An indicator that takes the value of one when an analyst moves to a larger brokerage in next year.	IBES
Demote	An indicator that takes the value of one when an analyst moves to a smaller brokerage in next year.	IBES
Terminate	An indicator that takes the value of one when an analyst disappear in the IBES next year.	IBES
Family wealth ($thousand)	The median household income in the census tract that an analyst resided in during his or her formative years, adjusted for 1950 dollars.	IBES, Linkedin, Classmate.com
High Family Wealth	An dummy variable which takes a value of 1 if an analysts' family wealth is above the sample median, and 0 otherwises.	IBES, Linkedin, Classmate.com
Gender	Analysts' gender	IBES, Linkedin
Connect	An indicator variable takes a value of 1 if an analyst attended the same university as the covered firm's executives or directors.	Boardex, IBES, Linkedin
General Experience	The number of years since an analyst has appeared in the IBES.	IBES
Firm Experience	The number of years since analysts has followed a firm.	IBES

Portfolio Size	The number of firms which analyst follows.	IBES
Top 10	Dummy variable that takes a value of 1 if an analyst works at a top decile brokerage house.	IBES
Forecast Horizon	The number of days from the forecast date to the earnings announcement date.	IBES