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Gender composition and conflicts of interest in the financial industry: Evidence from analysts' target price optimism[☆,☆☆]

Andria Charalambous[a], Alan Duboisée de Ricquebourg[a], Elvira Scarlat[b,*], Karin Shields[c]

[a] The Maurice Keyworth Building, Leeds University Business School, University of Leeds, Leeds LS2 9JT, United Kingdom
[b] Department of Accounting and Management Control, IE Business School-IE University, Maria de Molina 11-13, Madrid 28006, Spain
[c] Michael Young Building, The Open University Business School, Walton Hall, Milton Keynes MK7 6AA, United Kingdom

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ABSTRACT

A barrage of regulatory requirements has been issued to increase the impartiality of sell-side analysts' research reports and create a wall between equity research and investment banking departments. Yet studies suggest a persistent organizational culture within the profession that encourages optimistically biased research reports for current and potential investment banking clients. To examine potential solutions to this issue, we focus on sell-side analysts' target price optimism and find that analysts at brokerages with higher female representation issue significantly less optimistic target prices, especially when they face incentives to inflate forecasts due to their brokerage's affiliation to the firm being analyzed. To identify the mechanism behind this result, we explore analysts' optimism bias in situations when mergers between banks change gender composition in a way that is exogenous to the analysts, as well as when analysts voluntarily switch between brokerages with different gender compositions. The results of these analyses, along with a lag and forward test of the relation between the female proportion of analysts and optimism bias, indicate that gender composition plays a significant role in shaping brokerage culture. We rule out that results are driven by the gender of the individual analyst and confirm our results' robustness to various specifications. Our findings suggest the potential for gender composition of the workforce to aid self-regulation in the financial industry.

1. Introduction

> *"Eventually I started to see that the analyst's obligation to be independent, while ethically imperative, wasn't economically logical at all, given that he or she works for a firm whose primary purpose is to maximize fees."*
>
> (Reingold and Reingold, 2006, p. 302)

One of the biggest culprits behind the dot-com bubble was the irrational exuberance of financial analysts touting internet stocks underwritten by their investment banking colleagues (Global Analyst Research Settlement). In response, a barrage of regulations (Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, Reg FD)[1] was issued in 2003 to increase the impartiality of sell-side analysts' research and create a wall between the equity research and investment banking departments. These regulations prohibit analyst compensation and appraisals from being influenced by investment banking personnel or revenues and aim to prevent investment bankers from pressuring analysts to issue favorable stock recommendations. Despite these efforts, research shows that regulation has reduced—but not eliminated—the bias in recommendations attributed to conflicts of interest (Barniv et al., 2009; Chen and Chen, 2009) and that analysts still feel pressured to issue optimistic recommendations for their clients (Brown et al., 2015).

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* Corresponding author.
E-mail address: Elvira.Scarlat@ie.edu (E. Scarlat).

[1] NYSE Rule 472 and NASD 2711 have since been replaced by FINRA Rule 2241.

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In this paper, we explore the association between *gender composition* of brokerage workforces and analysts' optimism bias when facing conflicts of interest, which arise when analysts from the brokerage arm of a bank cover companies that are also clients of the bank's investment arm. This research is motivated by the literature showing that gender diversity has important outcomes for organizations (Altunbas et al., 2022) and that the male-dominated financial industry could benefit from greater gender diversity. Employee behavior is influenced by the ethics of top managers, known as "tone at the top" (Braumann et al., 2020; Garrett et al., 2022; Pyzoha et al., 2020), and this varies with the gender composition of boards. For example, Adams and Ferreira (2009) show that increasing female representation on boards leads to improved board effectiveness, due to female directors behaving differently but also because male directors act more diligently in the presence of female directors. However, the ethical climate is not exclusively set at the top: While tone at the top matters, ethical culture is created throughout the organization (Felo and Solieri, 2020). A growing literature recognizes that the gender composition of the workforce has important implications for the organizational climate of the firm. For example, Østergaard et al. (2011) show that diversity in gender and education among the workforce leads to better innovative performance, and Bai et al. (2022) show that ethics compliance costs for banks relate negatively to the diversity of both the board and workforce.

While male and female analysts are equally likely to achieve the prestigious AA (All American) status (Fang and Huang, 2017), the result around superior accuracy is not indisputable in the literature (Green et al., 2009), as subtle gender differences exist within the profession. The low representation of women among analysts suggests that female analysts may be more comparable to executives than the general population. Studies by Kumar (2010) and Gu (2020) find that forecasts made by female analysts tend to be more accurate and timely than those made by their male counterparts, although market perception of their abilities remains debated. These differences may be linked to variations in professional behavior. For example, female analysts are found to rely less on network connections than men (Fang and Huang, 2017), and appear more driven to issue precise earnings forecasts (Brown et al., 2015). Research on the impact of gender composition on analysts' performance is more limited. Notable exceptions include Fang and Hope (2021), who find that diversity, including gender, improves team performance, and Yao et al. (2024), who show that mixed-gender teams produce more accurate earnings forecasts with less bias. However, unlike these studies, this paper focuses on *individual analysts' performance* based on their brokerage's gender composition, rather than team performance. In this sense, our research is closely related to the study by Egan et al. (2022), who document a gender punishment gap in misconduct, and importantly, that this gap is mitigated by the gender composition of the managerial team.

The banking industry provides an ideal setting for examining our research question due to its inherent conflicts of interest. Underwriting by investment banks provides firms with vital access to financing (Painter, 2010), and an underwriter's reputation plays a critical role in the capital markets (Carter et al., 1998). However, optimistically biased equity research can yield benefits to the underwriter in terms of continued or future business (Ljungqvist et al., 2009) and to the affiliated analysts, who do not want to upset the underwriting arm of their brokerages or harm their careers (Brown et al., 2015).[2] Thus, a clash endures between analysts' self-serving interests and their responsibility to provide impartial research. Conflicts of interest are especially problematic in the context of the financial industry. Experiments show that, while bank employees are not dishonest in controlled settings, when their professional identity becomes salient, they are more likely to act dishonestly (Cohn and Juergens, 2014). This underscores the argument of Jennings (2013) that regulation alone cannot address the complex ethical issues faced by sell-side analysts and recalls the argument of Painter (2010) that moral responsibilities and self-supervision of investment bankers (or any profession) must complement regulation to eliminate misdeeds. In light of the limited success of regulation in this area, we ask an important question: Can a greater proportion of women in the workforce of brokerages enhance impartiality in equity research, even in the presence of pressures arising from conflicts of interest?

To test this question, we examine the relationship between target price optimism and the proportion of female analysts working for a brokerage. Target price optimism is a suitable measure for analysts' opportunism (Bradshaw et al., 2019). Our first test supports the choice of this setting for examining decision-making under conflicts of interest by showing that, in line with prior studies (Kadan et al., 2008), affiliated analysts do issue more optimistic target prices than their unaffiliated counterparts even in the post-regulatory period (i.e., after 2004). We thus confirm that regulatory reforms have had limited success in mitigating overly optimistic recommendations when the brokerage the analyst works for also receives revenue from the firm being analyzed.

Our main results show a statistically significant negative association between the rising proportion of female analysts employed by a given brokerage and target price optimism by both male and female analysts at that brokerage. The economic effects are significant: for an affiliated analyst, a one-standard deviation increase in the proportion of women in the brokerage, i.e., 7.7 percentage points, results in a reduction between 4 % and 12 % of the mean in the optimism bias measures.

We next explore the mechanism behind our results *via* a series of tests that tackle the endogeneity inherent in gender composition studies. First, we conduct a test using lagged and forward-looking values of the proportion of women in brokerages to examine its relation with optimism bias, and show that only the proportion of women leading up to the forecast significantly impacts optimism. This suggests that gender composition *shapes* brokerage culture rather than simply serving as a proxy for it. Second, examining analysts who voluntarily switch brokerages while continuing to follow the same companies, we find that differences in brokerages' gender composition significantly influence their optimism bias even when they continue to follow the same companies. Third, we investigate mergers between brokerages as a natural experiment to help us tackle endogeneity and separate the effect of analysts on brokerage culture from the possibility of analysts' self-selection into brokerages with certain cultures. Mergers lead to the creation of a new brokerage with a different gender composition, and the merger decision is independent from the analyst. Studying the behavior of retained analysts after this event, we observe a reduction in optimism bias among retained analysts at brokerages with an increase in female representation following the merger. While it is difficult to completely rule out endogeneity in our results, these additional analyses enhance the study's identification strategy and reduce endogeneity concerns by providing evidence that gender composition contributes to brokerage culture, which relates to analysts' optimism bias. We also refute the possibility that analysts' gender, rather than female representation overall, is driving our results by analyzing forecasts by male analysts separately as well as a subsample containing only forecasts for firms followed by both male and female analysts.

Finally, we find that the sanctions imposed on 12 banks for biased research by the 2003 Global Settlement do not explain our results and that our findings are robust to the use of different measures for female representation in the brokerage and to the use of different fixed effects. Further, our inferences are unaffected by excluding forecasts for the period of the financial crisis of 2008–2009. While times of crises might incentivize analysts to be more optimistic (Falconieri and De Amicis, 2023), we find that affiliated analysts at brokerages with a higher proportion of women exhibit less optimistic target prices both during and outside the financial crisis than their counterparts at brokerages with lower female representation. Taken together, our results suggest that

[2] We consider analysts as affiliated when, while employed at a brokerage, they follow a firm that is a client of the investment bank branch of the same brokerage institution.

firms with a greater proportion of women do better at self-regulation, with analysts at these brokerages providing less biased research.

Our paper contributes to the banking and finance literature focused on conflicts of interest and female representation. Conflicts of interest have long been debated due to the cost they impose on capital markets. Our result on the association between the proportion of female analysts and conflicts of interest measured by analysts' target price optimism bias is new. While many studies analyze gender and women's representation at the top, this is one of the few papers focusing on the role of employees *at all levels* of the brokerage in building corporate culture. A recent report shows that, while the representation of women in leadership, especially in the C-suite, has increased in many companies, women are still underrepresented (McKinsey, 2019). Our findings can inform policymakers about the role of gender representation at all levels of the corporation and on the dynamics between firm self-regulation and externally imposed regulation.

This paper is organized as follows: Section 2 discusses the literature, predictions and presumed mechanism. Section 3 explains the research design. Section 4 describes the sample selection and descriptive statistics. Section 5 presents the findings from our analysis. Section 6 concludes.

2. Literature review and prediction

The role of banks in financial markets has been widely debated, with two main views emerging in the literature: the certification effect and the conflicts of interest perspective. The certification effect suggests that banks can play a valuable role as certifiers of firm value, leveraging their access to information and monitoring capabilities to reduce information asymmetries (Gande et al., 1997; Puri, 1996). On the other hand, the conflicts of interest view posits that when banks act as both lenders and underwriters, they face conflicting incentives that may lead to biased decision-making, prioritizing their own interests over those of investors or clients. This is particularly problematic when banks have inside information or exert significant bargaining power over firms, potentially compromising the quality of financial services and leading to suboptimal outcomes (Mehran and Stulz, 2007; Rajan, 1992).

While this duality is crucial in the context of the financial industry, certain conditions are likely to exacerbate conflicts of interest in banking. A case in which the bank encourages optimistically biased research reports for companies that are current or potential clients of their investment banking colleagues is such a circumstance. The survey of equity analysts by Brown et al. (2015) shows that 44 % of respondents felt that success in generating underwriting or trading commissions for investment bankers influenced their compensation, directly at odds with regulation attempting to curb this conflict of interest. This point is further emphasized by an interview with a sell-side analyst:[3]

> Equity analysts . . . are very, very reluctant—even after the Spitzer rules—to upset the investment bankers, because the investment bankers bring in so much more profitability . . . They certainly realize that the success of their company is tied to the performance of this much higher margin business than the business that they're part of (Brown et al., 2015, p. 38).

Responses like this one demonstrate that analysts face conflicts of interest when producing research regarding companies that are also clients of their firms' investment banking arm. We interpret withstanding the pressure from the investment banking arm and issuing independent estimates as evidence of an analyst behaving more ethically. Cowen et al. (2006) question targeting regulation at analysts working for firms that provide underwriting, as reputational costs to investment banks should keep analysts' optimism in check. However, their tests do not consider the specific case in which the forecast is issued for a firm that is a client, and research confirms that analysts did succumb to this pressure before the regulatory reforms. Affiliated analysts were faster to upgrade and slower to downgrade their forecasts (O'Brien et al., 2005) and issued more optimistic earnings forecasts, growth earnings forecasts, and stock recommendations than their unaffiliated counterparts (Dugar and Nathan, 1995; Lin and McNichols, 1998; Michaely and Womack, 1999). Therefore, regulation alone has not fully resolved the persistent conflicts of interest in equity research.

Unethical decision-making costs capital markets billions of dollars a year and hurts corporations' credibility (Beu et al., 2003). At the same time, ethical conduct in banking is priced by shareholders (Kim et al., 2014). Regulatory reforms in the U.S. following the dot-com bubble aimed to resolve this issue by decreasing the interdependence between the research and investment banking departments in financial institutions (Global Analyst Research Settlement). However, the evidence regarding the overall effectiveness of the 2003 regulatory reform is mixed. For example, while Chen and Chen (2009) find that analysts' recommendations and earnings forecasts were less biased in the period following NASD 2711,[4] Barniv et al. (2009) find that the negative relation between stock recommendations and future returns persisted. Chen et al. (2018) likewise find that the association between analysts' outputs and corporate financing remained. Moreover, while regulatory reforms reduced the relative optimism of analysts' stock recommendations at sanctioned banks (Corwin et al., 2017; Guan et al., 2012),[5] analysts remained reluctant to issue pessimistic recommendations for their firms' investment banking clients (Kadan et al., 2008). Overall, the regulation mitigated some of the optimism bias in reports due to conflicts of interest, but conflicts of interest still exert undue influence over analysts' opinions.

Considering this evidence that investment bankers can still pressure analysts, we propose that the ethical climate of the corporate culture in brokerages is related to analysts' optimism when issuing target prices. Painter (2010) argues that regulation can set outer boundaries for behavior but that not all conduct within those boundaries is desirable. Bradshaw et al. (2019) refer to target price optimism as "self-serving behavior" and an example of "biased research" (Bradshaw et al., 2019, p. 85) and use an international sample to examine the importance of country institutions on the prevalence of this behavior. The results show that stronger investor protection and legal enforcement moderate target price optimism. However, we examine a U.S. sample, where target price optimism still prevails despite high scores on these dimensions and regulations targeted at increasing the cost of this self-dealing. Moreover, Cohn and Juergens (2014) provide compelling evidence that the honesty norm is weakened in the banking industry and call for measures to repair it. As Donaldson and Dunfee (2002) explain, at the core of ethical behavior in banking are *contracts* that bind industries and companies and generate ethical norms for their members. Confirming this view, a nudge reminding financial advisers of the bankers' oath reduces their likelihood to prioritize the bank's interests over the customer when faced with a conflict of interest (Weitzel and Kirchler, 2023).

What might improve moral judgments in business decisions? Several studies consider gender composition as a critical ingredient of corporate culture. Women are more inclined than men to interpret as unethical such misbehavior as taking bribes, breaking rules, and misusing private information (Arnaboldi et al., 2021; Atif et al., 2021; Cardillo et al.,

[3] FINRA 2241 (b) (C) "prohibit[s] persons engaged in investment banking activities from supervision or control of research analysts, including influence or control over research analyst compensation evaluation and determination."

[4] NASD Rule 2711 aimed to increase the independence of analysts' research and has since been replaced by FINRA 2241.

[5] All U.S. investment banks were subject to the new SRO rules. However, the 12 sanctioned banks included in the Global Analyst Research Settlement faced a $1.4 billion fine coupled with more requirements aiming to enhance the independence of their research departments. Initially the Global Settlement included 10 banks. However, two more banks were added in 2004.

2021; Hanousek et al., 2019). Compared to men, women are more concerned with corporate governance issues, monitoring, and corporate social responsibility (CSR) within their companies. Studies of gender differences in managerial opinions are rooted in stereotyped notions that women are more emotional and less competitive and ambitious, while men are more determined, competitive, and independent, which makes them less ethical than women (Mason and Mudrack, 1996; Weeks et al., 1999). This research generally concludes that women are less inclined than men to behave unethically (Beu et al., 2003; Dawson, 1997) and more likely to report misdeeds in companies (McDaniel et al., 2001).

Studies focused on highly competitive and risky industries (such as finance) do not necessarily find evidence of gender differences. For example, among sell-side analysts, Li et al. (2013) find no difference between the stock recommendation performance of males and females. In two recent studies, Avramov et al. (2018) find no evidence that gender is a source of systematic bias in analyst recommendations and Fang and Huang (2017) find no gender differences in forecasting accuracy. It is therefore plausible that women who self-select into top-level management positions or traditionally male professions in the financial industry do not share the same traits as the average woman (Adams and Funk, 2012; Croson and Gneezy, 2009; Sila et al., 2016) and more resemble their male counterparts. If so, female representation might not influence the ethics of brokerages.

However, women are *perceived* as more ethical, and men may therefore choose to conform to a higher standard of diligence and honesty in their presence. For example, banks perceive that female CFOs provide more reliable accounting information than their male counterparts (Francis et al., 2013), and board gender diversity improves bank performance (García-Meca et al., 2015). Importantly, men also behave differently in the presence of women. Adams and Ferreira (2009) show that an increasing proportion of female directors is associated with better meeting attendance by male directors and increased gender diversity on the board of directors is associated with fewer environmental violations (Liu, 2018) and fewer instances of securities fraud (Cumming et al., 2015). Further, gender-diverse boards are positively related to certain CSR dimensions (Francoeur et al., 2019), and *female participation* in setting the tone-at-the-top can improve the quality of financial information and conservatism (Krishnan and Parsons, 2008; Srinidhi et al., 2011). In the analyst profession, Jannati (2024) finds that the presence of female all-star financial analysts in a brokerage improves the earnings forecast accuracy and timeliness of peer analysts in the brokerage. Therefore, irrespective of gender differences in analysts' performance, the presence of women may incline their employers and peers toward greater ethics. This expectation comports with the prediction of Beltramini et al. (1984) that, following an increase in the number of women in the workforce, we would see a shift toward greater consideration of ethics in business decisions.

While tone-at-the-top matters, the ethical climate of the firm is not exclusively set by top management. A growing literature recognizes that the gender composition of the workforce has important implications for the climate of the firm. For example, Østergaard et al. (2011) show that diversity in gender and education among the workforce leads to better innovative performance, and Bai et al. (2022) show that ethics compliance costs for banks relate negatively to the diversity of both the board and the workforce. Gender diversity in the workplace (not only in the board room) mitigates firm carbon emissions (Altunbas et al., 2022). Considering these arguments, we expect that analysts working for brokerages with a higher proportion of female analysts will forecast target prices less optimistically, on average.

3. Research design

To examine this prediction, we use analysts' target prices to measure the bias of their research. Target prices provide a direct investment recommendation, whereas earnings forecasts are used as inputs in analysts' valuation models (Bilinski et al., 2019; Bradshaw, 2002; Brown et al., 2015). The outcome of target prices is also realized more often than that of earnings forecasts (Bradshaw, 2004; Lin and McNichols, 1998). Moreover, in the post-regulatory period, most investment banks shifted to a three-tier system of stock recommendations, making it harder to measure a change in analysts' bias using their recommendations (Bilinski et al., 2019; Kadan et al., 2008). By contrast, target prices allow us to estimate more accurately any changes in analysts' optimism. As for the reputational costs imposed by optimism bias, target prices are better suited than earnings forecasts or stock recommendations to capture conflicts of interest (Bilinski et al., 2019), as target prices do not count in the *Institutional Investor, The Wall Street Journal*, and StarMine analyst and broker rankings (Brown et al., 2015).

3.1. Dependent variables

We use four measures of target price bias. Following Bradshaw et al. (2019), the first two measures we construct reflect ex-ante analyst bias because they consider data available at the time of the forecast to assess the optimism of the analyst. First, *TP/P* is measured as an analyst's 12-month target price divided by the share price at the time of their forecast, minus one. Second, *TP/P_Rank* is based on the ranking of the *TP/P* relative to all other analysts within the same two-digit SIC industry and year. The most optimistically biased target prices will receive a rank of 99, and the least a rank of 1.

Next, we define two ex post measures of analyst optimism bias by considering how the stock price subsequently performed in relation to the target price. We modify the two binary measures used by Bradshaw et al. (2013), so that higher values represent greater optimism bias for ease of interpretation. *TP_NeverMet* is an indicator variable equal to one if the stock price over the next 12 months never equals or exceeds the target price. *TP_NotMetEnd* is an indicator variable equal to one if the stock price at the end of the 12-month forecast horizon is lower than the target price. Optimistically biased target price forecasts are expected to exceed the stock price at the end of the 12-month forecast horizon or the highest stock price over the 12-month forecast horizon.

3.2. Explanatory variables and model specification

To measure analysts' conflicts of interest, we follow Kadan et al. (2008) and O'Brien et al. (2005) by identifying all companies that issued equity, either through an IPO or an SEO, during the sample period. Analysts employed by either the lead underwriter or the co-manager of an equity issuance have been shown to exhibit Bias in their research (Bradley et al., 2008; Kadan et al., 2008; O'Brien et al., 2005), but the lead underwriter is subject to the greatest conflict of interest (Cliff, 2007; Ellis et al., 2000; Michaely and Womack, 1999). The lead underwriter oversees due diligence in IPO underwriting, price setting, and after-market price support (Michaely and Womack, 1999). Ellis et al. (2000) find that the lead underwriter plays the most significant role as a market maker, whereas the co-managers' role in the after-market trading of the IPO is negligible. Thus, even though all affiliated sell-side analysts are likely to have an incentive to provide optimistic research, the analysts employed by the lead underwriter face the greatest potential conflict of interest. Therefore, an analyst is defined as affiliated if they work for a brokerage that served as the lead underwriter for an equity issuance (IPO or SEO) of a firm they follow. Specifically, we assign a value of 1 to the indicator variable *(AFFILIATED)* if the analyst works for the lead underwriter of an IPO or SEO by a firm they follow within a two-year window; otherwise, the value is 0.

The main brokerage characteristic of interest is the proportion of female analysts (*FEM_PROP*). We define *FEM_PROP* as the percentage of female analysts in a brokerage in the year prior to the forecast. We also include *logBROKERSIZE*, which is measured as the natural logarithm of the number of analysts employed by an investment bank to control for the resources available to analysts in their research.

Table 1
Sample selection.

Panel A: Equity deals over the sample period 1st January 2003 to 31st December 2014		
	IPO	**SEO**
Initial sample	4,544	15,543
Less financial and utility firms	(1,815)	(4,916)
Less issues other than common stock	(170)	(2,191)
Less foreign (ADRs), withdrawn common, & US private stock	(684)	(4,555)
Less issuers with public status (excl. public, private, and subsidiary)	(6)	(85)
Less deals with missing Principal Amount information	(130)	(36)
Less deals other than firm commitment	(628)	(1,062)
Less deals with missing Lead Underwriter Information	(3)	(55)
Sample of equity deals to be matched with IBES and CRSP	**1,108**	**2,643**
Less deals not matched with IBES (based on CUSIP)	(142)	(72)
Sample of equity deals matched with I/B/E/S	**966**	**2,571**
Less deals with missing CRSP and 13F information	(186)	(718)
Final sample of equity deals	**780**	**1,853**

Panel B: Gender identification	
	Analysts
Initial sample of individual analysts	**11,597**
Less teams, departments, & analysts without a first initial	(1,109)
Valid analysts	**10,488**
Less unique analysts with no Capital IQ matches	(437)
Less analysts with the same initial and last names which cannot be matched	(298)
Matched analysts	**9,753**
Less analysts not on the Target Price Detail file	**(1,222)**
Sample of individual analysts to match with the equity deals	**8,531**

Panel C: Distribution of target price forecasts by analyst gender		
	Target price forecasts	**Analysts**
Analysts on the I/B/E/S Target Price Detail file	980,172	8,531
Less analysts without target prices for the sample of equity deals	(915,682)	(5,088)
Less firms with only one observation	(28)	(1)
Less target prices issued in 2003	(717)	(40)
Less singleton observation due to fixed effects	(1)	(0)
Analysts issuing target prices for sample equity deals	**63,744**	**3,402**
Male analysts	**57,883**	**3,001**
Female analysts	**5,861**	**401**

This table shows the sample selection process and distribution of analysts. Panel A shows the selection approach to identify the final sample of equity deals. Panel B shows the gender identification of unique analysts issuing target prices and/or stock recommendations over the sample period, 2003 to 2014. Panel C shows the number of unique analysts and the number target price forecasts they issued for the final sample of equity deals, as well as distribution of their gender over the sample period.

Individual analyst characteristics might also influence their target price bias. To control for this, we include five variables. First, as we study gender composition, we control for the analyst's gender by including an indicator variable (*FEMALE)* equal to one if an analyst is female and zero otherwise. We do not have an expectation regarding the sign of this variable's coefficient due to the mixed results discussed above regarding the existence of gender differences within the sell-side analyst industry and other high-profile male-dominated professions. However, if female analysts are more risk averse and conservative or if they are more ethical than their male peers, the coefficient would be negative. Another four variables control for an analyst's general experience (*logGEXP*), firm-specific experience *(logFEXP*), number of companies followed (*logCOVERAGE*), and their reputation (*ALL_STAR*). We measure *logGEXP* as the natural logarithm of an analyst's years of experience (Clement, 1999) and *logFEXP* as the natural logarithm of the number of years an analyst has followed the covered stock. Analysts with greater general and firm experience should issue better target price forecasts. Since it is less likely for an analyst to be as accurate when following many firms (Clement, 1999), we measure *logCOVERAGE* as the natural logarithm of the number of companies followed. Finally, *ALL_STAR* is an indicator variable to control for an analyst's reputation by taking the value of one if an analyst is identified as an All-Star in the issue of the *Institutional Investor* magazine in the previous year and zero otherwise (Fang and Yasuda, 2009), since analysts' All-Star status might improve their forecast accuracy (Xu et al., 2013).

Firm characteristics might also affect the accuracy and bias of analysts' target prices. Consequently, we include controls for price momentum (*PRCMOM*), the size of the company (*LOGMV*), stock price variability (*STDPRC)*, and institutional ownership (*INSTOWN_PCT).* *PRCMOM* controls for the ability of analysts to issue better target prices for stocks with more predictable price patterns (Bilinski et al., 2013). Analysts are also expected to issue less biased and more accurate target prices for stocks with high market value because of these stocks' richer information environments (Bradshaw et al., 2013). Thus, we control for the size of the company followed (*LOGMV*). Next, we control for higher analyst optimism for more volatile and risky stocks (*STDPRC*) and for market returns (*MRKRET*). Finally, institutional ownership (*INSTOWN_PCT*) may moderate analyst bias (Ljungqvist et al., 2007). All continuous independent variables are winsorized at the 1 percent level. Appendix A summarizes the dependent and independent variables used in this study.

The empirical specification of our multivariate regressions for analysts' optimism bias is:

$$OPTIMISM = \beta_0 + \beta_1 TRAIT + \beta CONTROLS + \sum FIRM + \sum YEAR + \varepsilon; \quad (1)$$

$$OPTIMISM = \beta_0 + \beta_1 TRAIT1 + \beta_2 TRAIT2 + \beta_3 (TRAIT1 \times TRAIT2) + \beta CONTROLS + \sum FIRM + \sum YEAR + \varepsilon. \quad (2)$$

OPTIMISM is one of our four measures of target price bias (*TP/P, TP/P_Rank, TP_NeverMet*, and *TP_NotMetEnd,)*, and *TRAIT* is one of the

Table 2
Sample description.

Panel A: Sample distribution by year							
Year		**Observations**	**Number of firms**	**Number of male analysts**	**Number of female analysts**	**Number of target prices by affiliated analysts**	**Number of target prices by unaffiliated analysts**
2004		3,206	324	802	93	553	2,653
2005		4,642	434	929	117	837	3,805
2006		4,195	463	934	122	906	3,289
2007		4,808	447	1,005	111	1,050	3,758
2008		5,334	384	971	110	1,011	4,323
2009		5,615	380	1,047	123	851	4,764
2010		6,645	385	1,192	130	1,167	5,478
2011		6,926	416	1,264	118	1,576	5,350
2012		6,126	387	1,127	112	1,488	4,638
2013		7,132	450	1,150	118	1,914	5,218
2014		9,115	506	1,203	123	2,557	6,558
Panel B: Sample distribution by industry							
Industry	**2-digit SIC**	**Observations**	**Number of firms**	**Number of male analysts**	**Number of female analysts**	**Number of target prices by affiliated analysts**	**Number of target prices by unaffiliated analysts**
Agriculture, Forestry and Fishing	01–09	23	2	7	0	8	15
Mining and Quarrying	10–14	11,329	115	457	32	1,681	9,648
Construction	15–17	855	27	92	14	233	622
Manufacturing	20–39	26,436	738	1,764	237	6,096	20,340
Transportation	40–49	858	19	175	11	181	677
Wholesale Trade	50–51	1,460	48	265	33	486	974
Retail Trade	52–59	4,078	93	314	78	1,117	2,961
Real Estate	60–67	605	31	166	16	194	411
Services	70–89	18,048	424	1,354	156	3,902	14,147
Public Administration	90–98	52	3	17	0	12	40

This table presents the sample distribution by year in panel A and by industry in panel B, including the number of firms followed, number of male and female analysts in the sample, and number of target prices issued by affiliated and unaffiliated analysts.

individual and brokerage traits (*AFFILIATED* and *FEM_PROP*). We use OLS regressions with firm and year fixed effects and report standard errors clustered at the firm level.

4. Sample and descriptive statistics

4.1. Sample selection

To identify analysts affiliated through an equity issuance, we first collected data from the SDC platform for all companies with an IPO or SEO in the U.S. during the sample period, 1 January 2004 to 31 December 2014.[6] The SDC platform gives information about the lead underwriters of an equity issuance, the offering technique (e.g., firm commitment, best efforts, etc.) and the date of issuance. When an issuance has more than one lead underwriter, the analysts employed by all the lead underwriters are all classified as affiliated.[7] The initial sample downloaded from SDC over the sample period included 4544 IPOs and 15,543 SEOs, as shown in Table 1 Panel A. From this initial sample we exclude financial and utility firms based on the issuer's main SIC code, foreign companies, and deals which did not involve common shares, Class A shares, ordinary shares, and ord. /common shares. To ensure complete equity issuances in the sample, we also remove deals with a missing or zero principal amount. Finally, we only retain those deals identified as firm commitments. Applying these criteria leaves a final sample of 1108 IPOs and 2643 SEOs over the sample period.

Following Kadan et al. (2008), we then merge this sample with the I/B/E/S detailed target price files, resulting in a matched sample of 966 IPOs (87 % match) and 2571 SEOs (97 % match) based on a company's CUSIP.[8] The CUSIP of the issuer and the name of the lead underwriter from SDC are then used to identify affiliated analysts. Since the brokerage names differ slightly between the two databases, we manually matched the underwriters' names from SDC (*bookrunners*) with the brokerage names in I/B/E/S (*estimid*). In the event of mergers between two investment banks, we follow Corwin et al. (2017) and assume that investment banking relationships from both predecessor banks were retained by the combined bank. As noted above, analysts are identified as affiliated if they are employed by the lead underwriter of an equity issuance and issued a target price for that stock within two years of the IPO or SEO.[9] Finally, unaffiliated analysts are included in the sample for those stocks for which an affiliated analyst was also identified (Corwin et al., 2017).

Next we merge in stock price data from CRSP and institutional ownership data from 13f Filings needed to construct our dependent and control variables. This further reduced the final sample to 780 IPOs and 1,853 SEOs. In total, both kinds of deals represented 1,453 unique stocks by CUSIP. Overall the final sample of equity deals included 58 unique

[6] The sample period starts in 2004 to avoid the disruption caused by the numerous regulatory reforms prior to that date. It ends in 2014 because the purpose of this study is to examine how internal factors within brokerage firms—particularly gender composition—address conflicts of interest that persisted despite major regulatory interventions (e.g., the Global Analyst Research Settlement, NASD Rule 2711, NYSE Rule 472, and Regulation FD). By focusing on internal dynamics, our sample covers a 10-year period following these interventions, capturing a relevant adaptation phase. This allows us to assess the correlation between gender composition and target price optimism without the confounding effects of later regulatory changes, such as MiFID II.

[7] For instance, in the IPO of Groupon in 2011, 11 lead underwriters were involved, whereas in Google's IPO in 2004, the number of lead underwriters was 10.

[8] Other studies included only one SEO per firm over their sample period (O'Brien et al., 2005). However, in this study, all the subsequent SEOs of the firms were included because in some cases the brokerage changes. Also, some firms have multiple SEOs within the same year. In those cases, if the lead underwriter is the same in all SEOs, which is usually the case, the latest SEO of that year was kept that is underwritten by the same lead underwriter.

[9] Equity issuances were therefore collected starting from 2001 to identify affiliated analysts from 2003.

investment banks involved in IPO underwriting, 80 unique investment banks involved in SEO underwriting, and 364 unique investment banks that employed the sample of affiliated and unaffiliated analysts following these companies.

We then used I/B/E/S and S&P Global Market Intelligence databases to identify the gender of the individual analysts who issued the target price forecasts for the final equity sample.[10] Among other information, the I/B/E/S detail files provide a unique identifier for each analyst, their current employer, as well as the analyst surname and the initial of their first name. Analyst gender, which is essential for the key variable in our study, is unavailable within the I/B/E/S detail files. We collect this information from the S&P Global Market Intelligence database, which provides analysts full names, job history, biographies, and a prefix specifying title (i.e., Mr., Mrs., and Ms.) that allows us to identify the analysts' gender.[11] In cases where the prefix was Dr., Prof., or blank, gender was identified from the biography provided by S&P Global.

Unfortunately, there is no easy way of linking the analysts between I/B/E/S and S&P Global other than by manually matching them based on last names, the initial of the first name, and employment history.[12] In those instances where analysts with unique names based on surname and initial of their first name were matched between the two databases, at least one job compatible between the two job histories was required for the analyst to be considered a valid match. If unique analysts matched but there was no common job between the two job histories, we conduct further research using FINRA's Broker Check. In other cases of duplicate names based on surname and initial of the first name, the I/B/E/S analyst with the most similar job history with the S&P Global analyst is matched. Where there was ambiguity as to which analyst was the best match, we remove the analyst from the sample.

Panel B of Table 1 summarizes the gender identification process. The initial sample exported from the I/B/E/S Target Price and Stock Recommendation Detail files over the sample period consists of 11,597 unique analysts by ID. Analyst IDs that related to teams and research departments or had missing first initial are excluded, as the gender identification is impossible in those instances (Sonney, 2009), leaving 10,488 valid analysts in the sample. From this sample, we can successfully identify the gender of 9753 analysts, representing a match of 93 % of valid analysts (i.e., analysts with surname and first initial), from which we then remove a further 1222 analysts who do not appear on the I/B/E/S Target Price Detail file over the sample period. We then merge this final sample of 8531 analysts and their associated 980,172 target prices with the 1,453 companies in our final sample of equity deals. This step results in our removing 5,088 analysts without target prices for the companies with equity deals and one analyst after removing 28 target prices for companies that only appeared once. Finally, we remove 717 target prices issued in 2003, as we rely on a lagged variable. We are therefore left with a final sample shown in Table 1 Panel C for our main analysis of 63,744 target prices issued by 3,402 unique analysts working for 364 brokerages, of which 89 % are men and 11 % are women.

[10] We created a comprehensive analyst gender list using all analysts from I/B/E/S Target Price and Stock Recommendation Detail files between 2003 and 2014, rather than directly identifying the gender of the unique analysts in the final equity sample, because, by using a limited sample of analysts covering certain stocks, other analysts appearing on I/B/E/S that are a better match with S&P Global sample analysts might be excluded, thereby assigning the wrong analyst from I/B/E/S to S&P Global.

[11] The S&P Global database was used by Lourie (2019), who utilized equity analyst employment history to test for analyst bias.

[12] While S&P Global provides the job history of the analyst, I/B/E/S provides the current employer as of the date that person submitted a forecast. To create a job history for the analysts in I/B/E/S, a unique code is used for each analyst, which does not change even if an analyst changes employers, thereby allowing identification of the brokerages for which an analyst has worked over the years.

4.2. Sample distribution

Table 2 Panel A presents the distribution of the 63,744 target prices over the sample period. Table 2 Panel B reports the distribution of target prices by industry and shows some industries with no or few forecasts made by female analysts. We address this in our analysis by repeating our main tests on a subsample of affiliated analysts for companies and years where both male and (at least one) female analysts issued target prices.

4.3. Descriptive statistics

Table 3, Panel A first presents the descriptive statistics of the ex-ante and ex-post bias measures, as well as our main variables of interest, *FEM_PROP* and *AFFILIATED*. The mean of *TP/P* shows analyst target prices expect stock prices to grow by an average of 21 % over their 12-month horizon, which is a good deal greater than the average annual stock price growth of around 10 % over the sample period. As for the characteristics of the brokerages in our sample (Coleman et al., 2023), Panel A of Table 3 also reveals that the average brokerage in our sample employs 8.6 analysts, with the largest one having 57 analysts (*Brokerage_size*). Two percent of the analysts in the average brokerage hold the *ALLSTAR* status (*Brokerage_ALLSTAR %)*. In terms of specialization, brokerages range between covering a single industry to 38 industries, with an average of seven and median of four industries (*Brokerage_specialization*). As for accuracy (*Brokerage_accuracy*), the mean earnings forecast error of analysts in the average brokerage represents 7 % of stock price, and analysts' experience has a mean of two years.

Moreover, a comparison between the affiliated and unaffiliated analysts (Panel B) shows that affiliated analysts forecast significantly higher growth (22.7 % versus 21.3 %). *TP/P_Rank* is also significantly greater for affiliated analysts, showing that they tend to issue more optimistic forecasts than unaffiliated analysts for firms in the same industry. The mean of *TP_NeverMet* shows no statistically significant difference between affiliated and unaffiliated analysts, even though, compared to the unaffiliated analysts, slightly more (36.1 % compared to 35.4 %) of the affiliated analysts' target prices were never met within the 12 months following their forecast. This gap increases and becomes significant when considering *TP_NotMetEnd,* with 63.9 % (65.8 %) of unaffiliated (affiliated) analysts' target prices not met at the end of the 12-month forecast horizon.

Table 3, Panel B further shows 10.5 % of target prices issued by affiliated analysts are by female analysts, which is significantly greater than the 8.8 % issued by women among target prices by unaffiliated analysts. Affiliated analysts on average have more experience and cover more stocks than unaffiliated ones. Additionally, affiliated analysts are employed by larger investment banks and brokerages with a higher proportion of women compared to unaffiliated analysts, which is unsurprising, given that larger and more prestigious investment banks are more likely to be the equity underwriters.

Table 3, Panel C shows the average annual percentage of female analysts as a share of the total number of analysts. Female analysts represent between 8.5 % (in 2011) and 11.6 % (in 2006) of total analysts on average in the brokerages of our sample, with a slight downward trend over time. Given the relatively low representation of female analysts within the profession, it remains unclear whether a higher proportion of female analysts within an investment bank can effectively reduce optimism bias in forecasted target prices. This is particularly relevant considering that a minimum gender composition of approximately 35 % female analysts may be necessary for a minority group to exert meaningful influence over workplace culture (Kanter, 1977). Panel C also shows the annual percentage of target prices issued by female analysts in the subsample of observations where analysts are affiliated with the firm they follow. This percentage closely aligns with the annual percentage of women in the overall sample, except in 2004,

Table 3
Differences in means for affiliated vs. unaffiliated analysts.

Panel A: Summary statistics

Variable	N	Mean	SD	Min.	Median	Max.
TP/P	63,744	0.213	0.323	−0.827	0.187	2.902
TP/P_Rank	63,744	49.098	28.871	0	49	99
TP_NeverMet	63,744	0.355	0.479	0	0	1
TP_NotMetEnd	63,744	0.643	0.479	0	1	1
FEM_PROP	63,744	0.112	0.077	0	0.105	1
AFFILIATED	63,744	0.218	0.413	0	0	1
Brokerage characteristics:						
Brokerage_size	1,648	8.654	10.963	1	4	57
Brokerage_ALLSTAR %	1,648	0.189	0.074	0	0	1
Brokerage_specialization	1,648	6.835	7.544	1	4	38
Brokerage_accuracy	1,571	−0.071	0.544	−9.132	0.003	2.328
Brokerage_experience	1,648	2.033	0.694	0	2.121	3.475

Panel B: Differences in means for affiliated vs. unaffiliated analysts

	Full sample	Affiliated sample	Unaffiliated sample	
Variable	**Mean**	**Mean**	**Mean**	**t-stat value**
TP/P	0.213	0.227	0.209	−5.820
TP/P_Rank	49.098	49.465	48.995	−1.698
TP_NeverMet	0.355	0.361	0.354	−1.465
TP_NotMetEnd	0.643	0.658	0.639	−4.083
FEM_PROP	11.19	13.49	10.55	−40.32
FEMALE	0.092	0.105	0.088	−6.143
ALL_STAR	0.07	0.165	0.044	−50.335
logGEXP	2.228	2.351	2.194	−19.115
logFEXP	0.837	0.763	0.857	14.726
logCOVERAGE	2.648	2.793	2.608	−26.365
logBROKERSIZE	2.923	3.609	2.732	−111.35
logMV	14.182	14.009	14.23	17.087
PRCMOM	0.117	0.106	0.12	4.668
STDPRC	0.027	0.027	0.028	7.721
MRKRET	0.117	0.114	0.118	3.624
INSTOWN_PCT	0.731	0.691	0.742	13.794
SANCTIONED	0.326	0.753	0.207	−138.68
N	63,744	13,910	49,834	
%	100 %	21.8 %	78.2 %	

Panel C: Annual gender distribution

Year	*Female analysts*	*Male analysts*	*Percentage of female analysts among total analysts*	*Percentage of forecasts made by female analysts in the affiliated subsample*
2004	93	802	10.4 %	7.6 %
2005	117	929	11.2 %	11.7 %
2006	122	934	11.6 %	11.8 %
2007	111	1,005	9.9 %	10.5 %
2008	110	971	10.2 %	9.0 %
2009	123	1,047	10.5 %	10.1 %
2010	130	1,192	9.8 %	13.0 %
2011	118	1,264	8.5 %	11.0 %
2012	112	1,127	9.0 %	10.6 %
2013	118	1,150	9.3 %	10.9 %
2014	123	1,203	9.3 %	9.3 %

Panel D: Pairwise correlations																
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) TP/P	1.00															
(2) TP/P_Rank	0.81***	1.00														
(3) TP_NeverMet	0.43***	0.42***	1.00													
(4) TP_NotMetEnd	0.37***	0.32***	0.55***	1.00												
(5) FEM_PROP	−0.02***	−0.04***	−0.03***	−0.03***	1.00											
(6) FEMALE	−0.01**	−0.01***	0.00	−0.01	0.20***	1.00										
(7) ALL_STAR	−0.05***	−0.05***	−0.04***	−0.04***	0.11***	0.03***	1.00									
(8) log*GEXP*	−0.02***	0.00	−0.02***	−0.02***	−0.03***	−0.05***	0.17***	1.00								
(9) log*FEXP*	−0.05***	−0.04***	−0.02***	−0.05***	−0.01**	−0.02***	0.10***	0.28***	1.00							
(10) log*COVERAGE*	0.01***	0.00	0.01**	0.01**	−0.04***	−0.09***	0.14***	0.54***	0.30***	1.00						
(11) log*BROKERSIZE*	−0.07***	−0.09***	−0.05***	−0.03***	0.11***	0.02***	0.21***	0.13***	0.02***	0.15***	1.00					
(12) log*MV*	−0.26***	−0.20***	−0.07***	−0.10***	0.02***	−0.02***	0.10***	0.05***	0.25***	0.04***	0.04***	1.00				
(13) PRCMOM	−0.24***	−0.18***	−0.10***	−0.07***	−0.01**	−0.01*	0.00	0.00	0.03***	0.01***	−0.02***	0.19***	1.00			
(14) STDPRC	0.20***	0.13***	0.02***	0.03***	0.00	−0.01***	−0.08***	−0.07***	−0.11***	−0.03***	−0.07***	−0.33***	0.04***	1.00		
(15) MRKRET	0.05***	0.05***	−0.14***	−0.19***	−0.02***	0.00	0.01***	0.00	0.08***	0.01**	−0.02***	0.04***	0.00	0.20***	1.00	
(16) INSTOWN_PCT	−0.09***	−0.06***	−0.04***	−0.04***	0.01*	0.01***	0.01***	−0.01	0.12***	−0.01**	0.00	0.12***	0.05***	−0.13***	−0.01***	1.00
(17) SANCTIONED	−0.08***	−0.09***	−0.06***	−0.04***	0.27***	0.05***	0.27***	0.04***	0.00	0.08***	0.57***	0.08***	−0.03***	−0.06***	−0.02***	0.00

This table presents summary statistics, with Panel A showing the mean and distribution of independent and explanatory variables of interest. Panel B presents the mean values of the dependent and control variables measured at each target price issue. Columns (1) to (4) shows the firm-analyst observations of the full sample and by affiliation. The *t*-value is obtained from independent *t*-tests in the mean values of the variables. Panel C presents the annual number of female and male analysts in our sample and the percentage of observations where the analyst is affiliated to the firm it follows made by female analysts. Panel D presents the pairwise correlations between all variables. See Appendix A for the variable definitions. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

Table 4
Association between affiliation and optimism bias.

	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	**0.011****	**0.823***	**0.014****	**0.015*****
	(2.484)	**(1.653)**	**(2.223)**	**(2.704)**
ALL_STAR	−0.009*	−1.314**	−0.017**	−0.024***
	(−1.652)	(−2.227)	(−2.142)	(−2.901)
logGEXP	0.002	0.489*	0.000	0.002
	(1.032)	(1.893)	(0.083)	(0.751)
logFEXP	0.014***	1.173***	0.005	−0.003
	(4.029)	(3.311)	(0.888)	(−0.616)
logCOVERAGE	0.003	0.310	0.010***	0.011***
	(1.219)	(1.161)	(2.669)	(3.286)
logBROKERSIZE	−0.023***	−2.519***	−0.023***	−0.014***
	(−9.439)	(−10.773)	(−7.145)	(−5.513)
logMV	−0.011	−0.368	0.273***	0.276***
	(−1.106)	(−0.504)	(17.859)	(15.382)
PRCMOM	−0.195***	−16.694***	−0.106***	−0.039**
	(−18.435)	(−18.863)	(−6.727)	(−2.191)
STDPRC	3.756***	198.692***	4.102**	3.317**
	(4.773)	(3.293)	(2.578)	(2.133)
MRKRET	0.310***	20.902***	−0.192***	−0.406***
	(8.357)	(7.951)	(−3.711)	(−8.895)
INSTOWN_PCT	−0.006	0.218	−0.023*	−0.012
	(−0.718)	(0.483)	(−1.927)	(−0.895)
Constant	0.297**	52.588***	−3.548***	−3.299***
	(2.006)	(4.892)	(−15.176)	(−12.182)
Observations	63,744	63,744	63,744	63,744
R-squared	0.458	0.275	0.281	0.337
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table shows the result of regressing the five optimism bias measures on whether the analyst was affiliated, i.e. employed by the lead underwriter in a seasoned equity offering or initial public offering by the firm for which the analyst is issuing the target price. All models include the control variables and the firm and year fixed effects as per Eq. (1). T-statistic in parentheses. Standard errors clustered at the firm level. All variables are defined in appendix A. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

Table 5
Analysis of female representation and optimism bias.

Panel A: Analysis of affiliation and proportion of female analysts	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.052***	4.925***	0.067***	0.056***
	(4.911)	(4.415)	(4.328)	(3.902)
FEM_PROP	−0.029	−6.357***	−0.100***	−0.060**
	(−1.328)	(−2.885)	(−3.615)	(−2.230)
AFFILIATED* × *FEM_PROP	**−0.293*****	**−28.898*****	**−0.369*****	**−0.286*****
	(−3.928)	**(−3.627)**	**(−3.475)**	**(−2.784)**
FEMALE	−0.006	−0.836	0.003	−0.006
	(−1.014)	(−1.237)	(0.392)	(−0.791)
Constant	0.295**	52.817***	−3.543***	−3.297***
	(1.997)	(4.927)	(−15.202)	(−12.199)
Controls included	YES	YES	YES	YES
Observations	63,744	63,744	63,744	63,744
R-squared	0.459	0.276	0.281	0.337
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Affiliated subsample	**TP/P**	**TP/P_Rank**	**TP_NeverMet**	**TP_NotMetEnd**
FEM_PROP	**−0.275*****	**−28.789*****	**−0.440*****	**−0.558*****
	(−3.095)	**(−2.913)**	**(−3.105)**	**(−3.955)**
FEMALE	−0.024*	−3.739**	−0.011	−0.008
	(−1.883)	(−2.323)	(−0.561)	(−0.429)
Constant	0.572***	76.004***	−3.478***	−3.084***
	(2.891)	(4.513)	(−11.290)	(−9.563)
Controls included	YES	YES	YES	YES
Observations	13,810	13,810	13,810	13,810
R-squared	0.551	0.406	0.364	0.385
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table reports the regression results on the determinants of target price optimism including *FEM_PROP* on forecasts made by the full sample of affiliated and unaffiliated analysts (Panel A), the subsample of affiliated analysts only (Panel B). All models include the control variables and the firm and year fixed effects as per Eqs. (1) and 2. T-statistics in parentheses. Standard errors are clustered at the firm level. All variables are defined in appendix A. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

when it is lower (7.6 % compared to 10.4 % in the main sample), and during the years 2010–2013, when it exceeds the percentage of women in the main sample. Finally, Table 3, Panel D presents a correlation matrix which reveals a positive and significant correlation between all our optimism measures which are all negatively correlated to *FEM_PROP*. We also note that *FEM_PROP* is positively correlated with *logBROKERSIZE*, reflecting that larger brokerages employ more female analysts.

5. Results and discussion

5.1. The impact of analysts' affiliation on optimism bias

We begin our analysis by examining the association between analysts' affiliation and the level of optimism bias in their target prices by estimating Eq. (1). Like prior research (Cliff, 2007; Corwin et al., 2017; Michaely and Womack, 1999), our results, presented in Table 4, show that analysts' affiliation is associated with greater optimism among all four measures. This gives us confidence that our optimism measures capture the additional optimism conveyed by analysts when faced with the conflict of interest documented by prior literature. For instance, affiliated analysts are likely to be ranked (*TP/P_Rank*) 0.823 points higher on the 1–99 scale of target price optimism compared to their unaffiliated counterparts. Moreover, compared to unaffiliated analysts, affiliated analysts' target prices are less likely to be met at the end (*TP_NeverMet*) or exceeded within the 12-month forecast horizon (*TP_NotMetEnd*) (coef. 0.014, t-stat. 2.223 and coef. 0.015, t-stat. 2.704, respectively). This may be partly explained by the fact that, when compared to their unaffiliated peers, affiliated analysts' target prices exceed the current share prices (*TP/P*) by an additional 1.1 percentage points (coef. 0.011, t-stat. 2.484). Overall, these results validate the suitability of our chosen setting and support the notion that conflicts of interest for affiliated analysts persist despite regulatory interventions and lead to overly optimistic target prices issued by affiliated analysts compared to unaffiliated analysts.[13]

5.2. The impact of female representation on optimism bias

Our main analysis examines whether a higher proportion of female analysts within an investment bank can reduce the optimism bias in forecasted target prices. We measure female representation (*FEM_PROP)* as the annual percentage of female sell-side analysts employed in an investment bank during the previous calendar year to account for the

[13] Cowen et al. (2006) show that brokerage characteristics are associated with analyst optimism. They find that analysts working for investment banks are less optimistic than those working for syndicate banks, retail brokerages, or research-only firms, suggesting that optimism is driven by incentives larger than underwriting relationships, such as trading. Appendix B shows the results for the analysis with the addition of broker-fixed effects, which confirm that analysts produce significantly more optimistic forecasts for firms that are also underwriting clients of the brokerage arm, validating the suitability of this setting for our research question.

Table 6
Lagged and forward-looking *FEM_PROP*, affiliated subsample.

	TP/P_{t-3}	TP/P_{t-2}	TP/P_{t-1}	TP/P_{t0}	TP/P_{t+1}	TP/P_{t+2}	TP/P_{t+3}
FEM_PROP	**−0.298****	**−0.408*****	**−0.355*****	**−0.250***	**−0.12**	**−0.161**	**−0.052**
	(−2.380)	**(−3.151)**	**(−2.850)**	**(−1.746)**	**(−0.671)**	**(−0.931)**	**(−0.299)**
FEMALE	−0.019	−0.015	−0.014	−0.017	−0.019	−0.02	−0.021
	(−1.032)	(−0.794)	(−0.770)	(−0.916)	(−1.041)	(−1.083)	(−1.126)
Constant	0.503*	0.272***	0.502*	0.493*	0.487*	0.487*	0.488*
	(1.861)	(14.757)	(1.853)	(1.816)	(1.797)	(1.798)	(1.791)
Controls included	YES	YES	YES	YES	YES	YES	YES
Observations	7,155	7,155	7,155	7,155	7,155	7,155	7,155
R-squared	0.588	0.543	0.589	0.588	0.588	0.588	0.588
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

This table reports the regression results on the determinants of lagged and forward values of target price optimism including *FEM_PROP*. The model includes the control variables and the firm and year fixed effects. T-statistics in parentheses. Standard errors are clustered at the firm level. All variables are defined in appendix A. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

culture prior to and during the target price issuance of a given analyst.[14] Table 5, Panel A reports the results of estimating Eq. (2) for the full sample and shows that, while *AFFILIATED* relates positively to all four optimism bias measures, *FEM_PROP* is negatively associated with optimism bias among three measures. This is important because optimism bias is not solely a problem where the analyst is affiliated through an underwriting relationship (Cowen et al., 2006). However, our main coefficient of interest is the interaction between *AFFILIATED* and *FEM_PROP*, which is negative and significant for all four measures and indicates that the percentage of female analysts employed by a brokerage attenuates optimism bias and that this moderating effect is enhanced where there is a conflict of interest. We also control for the gender of the analyst, which is not significantly different from zero in this model. Overall, biased research appears to be significantly lower in brokerages with more female analysts within their workforce.[15] We also estimate the economic significance of the female proportion on target price optimism as a percentage of the mean in the dependent variable explained by a one standard deviation change in the independent variable in the regressions. For an affiliated analyst, a one standard deviation increase in the proportion of women in the brokerage, i.e. 7.7 percentage points, results in a reduction of between 4 % and 12 % in the mean of the optimism bias measures.[16]

Next, Table 5, Panel B, presents the results for estimating Eq. (1) on the subsample of affiliated analysts and shows that *FEM_PROP* is significantly and negatively associated with all four optimism bias measures, confirming its effectiveness in mitigating optimistically biased research in the presence of conflicts of interest. In the first column, the dependent variable is the implicit return (*TP/P*) and the coefficient for *FEM_PROP* is −0.275 (t-stat. −3.95). This means that a standard deviation increase in *FEM_PROP* is associated with predicted returns that are 2.7 percentage points lower. The average predicted return in this subsample is 22.7 %. Therefore this standard deviation increase in *FEM_PROP* represents a 9.32 % reduction in *TP/P*. Similarly, a standard deviation increase in *FEM_PROP* is associated with a 4.48 % reduction in an analyst's *TP/P_Rank*, a 9.4 % reduction in the likelihood of the target price never being met (*TP_NeverMet*) and a 6.53 % reduction in the likelihood of target price not being met at the end of the 12-month forecast period (*TP_NotMetEnd*). We also observe that female analysts in this subsample tend to be less optimistic, although this is only significant for two of the four optimism measures. We explore this further in Section 5.4.

5.3. Mechanism and endogeneity

In this section, we delve into the mechanism driving our main findings while simultaneously addressing potential endogeneity concerns inherent to the study's context. Specifically, we: (1) analyze lagged and forward values of the key variables to assess the temporal dynamics of the observed relationships, (2) investigate changes in workplace and gender composition resulting from analysts moving between brokerages, and (3) leverage an exogenous shock to gender composition caused by mergers and acquisitions among brokerages. Together, these analyses provide an understanding of whether analysts create workplace culture or self-select into brokerages of pre-existing cultural attributes.

Our first analysis examines the relation between optimism bias and the proportion of women in the brokerage over a six-year window, spanning three years prior to and three years following the forecast. This analysis aims to disentangle two key possibilities: (1) whether gender composition serves primarily as a proxy for the brokerage's existing culture (into which analysts might self-select), or (2) whether gender composition itself plays a formative role in shaping that culture. If gender composition merely reflects the brokerage's existing culture, we would expect both the lagged and forward values of *FEM_PROP* to be associated with optimism. However, if changes in gender composition actively shape the brokerage culture (and optimism), we would anticipate that only the proportion of women in the years leading up to the forecast would show a significant association with optimism.

Table 6 provides evidence supporting the latter interpretation. It shows that the proportion of women in the brokerage during the years leading up to and including the forecast year, has a significant impact on analyst optimism. In contrast, the proportion of women in the years following the forecast exhibits no significant association. This pattern suggests that, on average, it is the proportion of women shaping brokerage culture—thereby reducing optimism bias—rather than the existing culture simply attracting more female analysts in subsequent years or gender composition representing solely a proxy for culture.[17]

Second, our next test explores cases when analysts voluntarily switch brokerages but continue to follow the same company. This setting allows us to explore heterogeneity in analysts' cross-sections to isolate the

[14] *FEM_PROP* is calculated based on the number of analysts working at the research department who submit a forecast on I/B/E/S, rather than the number of employees within the whole investment bank. Therefore, when referring to organizational culture, this study refers to the culture of the research department that employs the sell-side analysts. Arguably, regulations attempted to increase the independence of the research department from the other departments within the investment bank, which might shape the culture of the research department differently.

[15] Our results are robust if we cluster errors by firm and analyst.

[16] The one standard deviation increase in FEM_PROP is associated with the following reduction as a percentage of the mean for each of the four optimism measures: 11.64% for *TP/P*, 5.53% for *TP/P_Rank*, 10.17% for *TP_NeverMet*, and 4.14% for *TP_NotMetEnd*.

[17] This analysis was conducted across all optimism measures, with *FEM_PROP* found to be significant only in the years prior to the forecast. For brevity, we present results for the *TP/P* measure only.

Table 7
Endogeneity.

Panel A: Analysts that switch brokerages	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.076*	10.051**	0.171***	0.135**
	(1.717)	(2.308)	(2.657)	(2.252)
FEM_PROP	**−0.085***	**−7.243**	**−0.154****	**−0.108**
	(−1.651)	**(−1.489)**	**(−2.230)**	**(−1.467)**
AFFILIATED × FEM_PROP	**−0.590****	**−68.660****	**−1.038****	**−0.757***
	(−2.012)	**(−2.264)**	**(−2.396)**	**(−1.779)**
FEMALE	0.035	3.224	0.070**	0.048*
	(1.254)	(1.121)	(2.240)	(1.778)
Constant	0.031	20.157	−4.628***	−3.970***
	(0.125)	(1.000)	(−11.403)	(−9.783)
Controls included	YES	YES	YES	YES
Observations	7,964	7,964	7,964	7,964
R-squared	0.491	0.363	0.335	0.379
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Analysts that move to brokerages with higher proportion of female analysts				
	TP_P	**TP_P_Rank**	**TP_NeverMet**	**TP_NotMetEnd**
POST	−0.056***	−3.037	−0.019	−0.054
	(−2.687)	(−1.380)	(−0.450)	(−1.402)
AFFILIATED	0.060*	9.728***	0.058	−0.068
	(1.847)	(2.995)	(0.926)	(−1.164)
POST × AFFILIATED	**−0.137****	**−16.451*****	**−0.186****	**0.067**
	(−2.273)	**(−2.825)**	**(−2.284)**	**(0.745)**
Constant	−0.449	−7.467	−5.321***	−5.239***
	(−1.256)	(−0.223)	(−9.405)	(−8.594)
Controls included	YES	YES	YES	YES
Observations	1,915	1,915	1,915	1,915
R-squared	0.576	0.487	0.414	0.483
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel C: Retained analysts after brokerage mergers				
	TP/P	**TP/P_Rank**	**TP_NeverMet**	**TP_NotMetEnd**
FEM_PROP	−0.237	−24.201	−0.193	0.161
	(−1.362)	(−1.539)	(−0.968)	(0.771)
AFFILIATED	0.109	23.062**	0.132	0.477***
	(1.092)	(2.079)	(0.795)	(3.011)
AFFILIATED × FEM_PROP	**−1.414***	**−187.973****	**−0.873**	**−4.026*****
	(−1.682)	**(−2.208)**	**(−0.668)**	**(−3.526)**
Constant	−0.332	−16.639	−5.915***	−4.379***
	(−0.702)	(−0.449)	(−6.196)	(−5.949)
Controls included	YES	YES	YES	YES
Observations	1,486	1,486	1,486	1,486
R-squared	0.630	0.531	0.452	0.499
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel D: Retained analysts in brokerages with higher resulting FEM_PROP than that of the target brokerage				
	TP/P	**TP/P_Rank**	**TP_NeverMet**	**TP_NotMetEnd**
FEM_PROP	0.001	−12.340	0.475	−0.199
	(0.003)	(−0.273)	(0.818)	(−0.409)
AFFILIATED	0.504	69.559*	1.378**	0.906**
	(1.663)	(1.983)	(2.278)	(2.088)
AFFILIATED × FEM_PROP	**−3.661***	**−557.671****	**−10.251****	**−8.334****
	(−1.934)	**(−2.560)**	**(−2.636)**	**(−2.714)**
Constant	−1.094	−59.725	−6.326***	−3.996*
	(−1.180)	(−0.623)	(−4.543)	(−1.912)
Controls included	YES	YES	YES	YES
Observations	314	314	314	314
R-squared	0.705	0.582	0.493	0.560
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table reports the regression results on the determinants of target price optimism including *FEM_PROP* on forecasts made by the subsample of analysts that follow the same firm after switching brokerages. Panel A shows the results for observations of target prices two years before and two years after any switch made by analysts. Panel B shows results for replacing the FEM_PROP variable with *POST* which takes 1 if the target price forecast is made after the merger into the new brokerage, with the first four panels showing the results for merging into a brokerage with a higher proportion of women and the four last columns, a switch to a brokerage with a lower proportion of women. Panel C includes only observations by analysts that moved due to a merger or acquisition of their former brokerage. Panel D shows the results for analysts that were retained in a merger or acquisition that experienced an increase in the proportion of female analysts. All models include the control variables and the firm and year fixed effects as per Eqs. (1) and 2. T-statistics in parentheses. Standard errors are clustered at the firm level. All variables are defined in appendix A. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

Table 8
Analysts' gender and optimism bias.

Panel A: Analyst gender, affiliation and target price optimism bias				
	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.012**	0.980*	0.014**	0.013**
	(2.464)	(1.884)	(2.095)	(2.236)
FEMALE	**−0.008**	**−0.944**	**−0.003**	**−0.015***
	(−1.197)	**(−1.261)**	**(−0.367)**	**(−1.760)**
AFFILIATED × FEMALE	**−0.001**	**−1.312**	**0.002**	**0.022**
	(−0.110)	**(−0.877)**	**(0.106)**	**(1.321)**
Constant	0.296**	52.502***	−3.548***	−3.297***
	(2.004)	(4.882)	(−15.179)	(−12.178)
Controls included	YES	YES	YES	YES
Observations	63,744	63,744	63,744	63,744
R-squared	0.458	0.275	0.281	0.337
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Male analysts				
	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.052***	4.469***	0.062***	0.051***
	(4.667)	(3.769)	(3.764)	(3.341)
FEM_PROP	**−0.039**	**−8.608*** **	**−0.111*** **	**−0.048***
	(−1.597)	**(−3.525)**	**(−3.519)**	**(−1.650)**
AFFILIATED × FEM_PROP	**−0.295*** **	**−25.005*** **	**−0.344*** **	**−0.285** **
	(−3.659)	**(−2.862)**	**(−2.932)**	**(−2.494)**
Constant	0.317**	53.983***	−3.562***	−3.356***
	(2.081)	(4.892)	(−14.751)	(−11.894)
Controls included	YES	YES	YES	YES
Observations	57,874	57,874	57,874	57,874
R-squared	0.457	0.280	0.283	0.339
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel C: Firms followed by both male and female analysts				
	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.062***	6.540***	0.085***	0.094***
	(3.963)	(3.884)	(3.889)	(4.366)
FEM_PROP	**−0.043**	**−7.529** **	**−0.132*** **	**−0.059***
	(−1.402)	**(−2.490)**	**(−3.563)**	**(−1.654)**
AFFILIATED × FEM_PROP	**−0.347*** **	**−38.798*** **	**−0.458*** **	**−0.523*** **
	(−3.191)	**(−3.354)**	**(−3.053)**	**(−3.390)**
FEMALE	−0.003	−0.681	0.008	−0.003
	(−0.563)	(−0.987)	(0.898)	(−0.392)
Constant	0.279	47.642***	−3.699***	−3.579***
	(1.326)	(3.193)	(−11.370)	(−9.940)
Controls included	YES	YES	YES	YES
Observations	32,157	32,157	32,157	32,157
R-squared	0.454	0.257	0.290	0.339
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table reports the regression results of analyst gender (*FEMALE*) on forecast optimism using the full sample of affiliated and unaffiliated analysts (Panel A). In Panel B, we use the subsample of male analysts in affiliated and unaffiliated brokerages, 9 singleton observations were dropped. In Panel C we retain only firms followed by analysts of both genders. All models include the control variables and the firm and year fixed effects as per Eqs. (1) and 2. All variables are defined in appendix A. T-statistic in parentheses. Standard errors clustered at the analyst and firm level. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

variation in optimism bias attributable to the brokerage's gender composition: since different brokerages have different levels of female representation, and we hold individual characteristics and the firm being followed constant, differences in the analyst's optimism bias are likely attributable to the brokerage gender composition. We identify analysts who switch brokerages during the sample period but maintain their coverage of a given firm. Only forecasts made two years before and two years after the switch are included. There are 611 analysts who meet these requirements, and they cover 581 companies. Panel A of Table 7 reports the results. The coefficients of the interaction are negative and significant in all regressions, despite the reduction in sample size imposed by creating this sample. Moreover, the magnitudes of the significant coefficients are at least twice as large as those in Table 5, validating the notion that this specification better targets brokerage culture and demonstrates the robustness of our previous findings.[18] In Table 7, Panel B we present results from analysis of a subsample of the analysts that switch brokerages containing only those analysts that move to a brokerage with a higher proportion of women. Coefficients of the interaction are negative and significant for 3 of our 4 optimism measures, providing further support for the notion that analysts respond to the culture of the brokerage which is affected by its workforce gender composition.[19]

Third, we study the effect of an exogenous event that affects gender composition in the brokerage, drawing on the specialized literature that addresses endogeneity concerns (Hong and Kacperczyk, 2010; Wang et al., 2020). Specifically, we investigate mergers between brokerages as a natural experiment to help us tackle endogeneity and separate the effect of analysts on brokerage culture from the possibility of analysts' self-selection into brokerages with certain cultures. Mergers lead to the creation of a new brokerage house with a different culture (Chen et al., 2018) and, importantly for our setting, a different gender composition. Also, the merger decision is independent of the analyst. Analysts from the target brokerage that are *retained* in the resulting brokerage find themselves part of a new department, with a new culture and gender composition. As such, the merger represents a shock to gender composition (*FEM_PROP*) that allows us to study whether such exogenous changes influence the optimism bias for retained analysts. Because retained analysts generally continue to follow the same companies (Hong and Kacperczyk, 2010), finding a reduction in optimism bias in this setting would strongly suggest that this effect results from changes in the gender composition of the resulting brokerage house.

We use SDC to identify 18 mergers between brokerage houses over our sample period, and 86 analysts from target brokerage houses are retained into the department of the resulting brokerage. We then estimate the effect of gender composition and analyst affiliation on the optimism of the 86 retained analysts. This reduces our sample to 1486 observations. Results are presented in Table 7, Panel C. We find a significant reduction in optimism among retained analysts working for brokerages with a higher proportion of female analysts.

To further diagnose whether this result stems from analysts who

[18] One characteristic of this setting is that the analyst will not be affiliated with both brokerages; in untabulated tests, we also estimate the regression including *AFFILIATED* only as a control variable, rather than interacted with *FEM_PROP*. The main variable of interest becomes *FEM_PROP*, and the results comport with the findings presented above. Additionally, section 5.5 includes analysis of this setting additionally controlling for analyst-fixed effects, results are qualitatively similar.

[19] We also explore the global financial crisis. First, we confirm that the financial crisis does not interfere with our main result by excluding the forecasts for the period of the financial crisis (2007 and 2008, because we remove ex-ante optimism ahead of a crisis that analysts could not have foreseen). Results in Appendix D, Panel A consistently show a decrease in the four optimism bias measures for affiliated analysts at brokerages with higher female proportion in the workforce. Second, we verify whether our results change in times of crises, which generally incentivize analysts to be more optimistic (Falconieri & De Amicis, 2023). As shown in Panel B of Appendix D, we find that analysts at brokerages with higher proportion of women are less optimistic during the financial crisis than their counterparts from brokerages with lower *FEM_PROP*, even when they are affiliated. This result suggests that gender composition plays a relevant role in analysts' optimism in times of crisis.

Table 9
Analysis of sanctioned banks.

Panel A: Sanctioned banks	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.048***	4.543***	0.060***	0.050***
	(4.531)	(4.078)	(3.887)	(3.493)
FEM_PROP	**−0.009**	**−3.921***	**−0.072****	**−0.040**
	(−0.415)	**(−1.792)**	**(−2.568)**	**(−1.487)**
AFFILIATED × FEM_PROP	**−0.278*****	**−23.534****	**−0.388*****	**−0.340*****
	(−3.283)	**(−2.551)**	**(−3.170)**	**(−2.917)**
SANCTIONED	**−0.031*****	**−3.721*****	**−0.043*****	**−0.029*****
	(−5.786)	**(−6.391)**	**(−5.688)**	**(−4.455)**
AFFILIATED × SANCTIONED	**0.017***	**1.275**	**0.033****	**0.032****
	(1.686)	**(1.123)**	**(2.259)**	**(2.441)**
FEMALE	−0.007	−0.875	0.003	−0.006
	(−1.066)	(−1.295)	(0.343)	(−0.829)
Constant	0.280*	50.965***	−3.563***	−3.310***
	(1.900)	(4.771)	(−15.313)	(−12.269)
Controls included	YES	YES	YES	YES
Observations	63,744	63,744	63,744	63,744
R-squared	0.459	0.277	0.282	0.338
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

This table shows the results of the analysis based on augmenting Eq. (2) with the variable *SANCTIONED* and the interaction term *AFFILIATED*SANCTIONED*. Panel B shows the results of regressing the optimism measures on *SANCTIONED* and FEM_BROKERAGE, an indicator variable which takes 1 if the brokerage is in the top tercile percentage of female analysts. Panel C shows results for the subsample of brokerages that were not sanctioned. All models include the control variables including analyst gender and the firm and year fixed effects as per Eqs. (1) and (2). All variables are defined in appendix A. T-statistic in parentheses. Standard errors clustered at the firm level. ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels.

experience an *increase* in the proportion of women in their workplace, we retain only mergers where the resulting brokerage house had a higher proportion of women than the target; in other words, the retained analyst was working at a brokerage and experienced an increase in *FEM_PROP* after the merger. Results of this partition, presented in Table 7, Panel D, reveal an even stronger drop in optimism across the four metrics. Notably, this stronger effect is observed despite the small number of observations, underscoring the robustness and consistency of the findings even in a highly selective and focused setting.

5.4. Further analyses

5.4.1. Analysts' gender and optimism bias

We next explore the possibility that analysts' gender, rather than female representation, drives our results. A potential explanation for the results could be the gender punishment gap outlined in Egan et al. (2022). To test whether this drives our results, we estimate the moderating effect of analyst gender (*FEMALE*), instead of the proportion of female analysts (*FEM_PROP*), in Eq. (1).[20] Table 8, Panel A, shows that the coefficients for *AFFILIATED* remain positive and highly significant along all measures of optimism bias, but the interaction term *AFFILIATED × FEMALE* is insignificant across all specifications. Therefore, consistent with the self-selection theory that posits that analysts with certain traits (irrespective of gender) choose careers in this industry, we find no evidence that female and male financial analysts issue differently biased forecasts. Rather, it is the greater proportion of women that influences the overall optimism of forecasted target prices.

Finally, if the proportion of women were related to the ethical culture in the organization, then results would not be driven by the subsample of female analysts; instead norms in brokerages with a greater proportion of women would be likely to influence all analysts, men included. To verify this, we examine the association between *AFFILIATED × FEM_PROP* and optimism bias for the subsample of *male* analysts only. The analysis in Table 8, Panel B, shows that the association is again negative and statistically significant for all four optimism measures. This result, together with the lack of significance of the variable *FEMALE* in Table 5, reveals that a higher proportion of female analysts mitigates the bias displayed by *all* analysts. This is consistent with female participation positively influencing the organizational culture and norms.[21][22]

Finally, to rule out drawing incorrect inferences about gender relevance for our conclusion due to analysts' self-selection into following certain stocks or working for certain brokerages, we also examine a subsample of forecasts issued only for firms covered by analysts of both genders. Results in Table 8, Panel C, show that the interaction term *AFFILIATED × FEM_PROP* is significantly negative for all optimism measures, supporting the idea that our main conclusions are not driven by analysts' gender.

5.4.2. Sanctioned banks

Regulatory changes introduced in 2003 targeted the mitigation of optimism bias in affiliated brokers. Although all U.S. banks had to comply with the new NASD 2711 rules, 12 banks (10 initially, with two more added in 2004) were sanctioned and faced a $1.4 billion fine, coupled with more requirements aiming to enhance the independence of their research. Chen and Chen (2009) and Chen et al. (2018) find that analysts' recommendations and earnings forecasts were less biased in the period following NASD 2711, but the evidence is mixed. Therefore, we explore whether these sanctions also mitigate optimism bias among analysts at the brokerage arm of these banks and how that relates to the

[20] In this specification, we replace *FEM_PROP* with *FEMALE* to avoid multicollinearity between these two variables biasing the result.

[21] Despite the fact that brokerage fixed effects might absorb the enduring part of organizational culture, we verify the robustness of our results to the inclusion of brokerage fixed effects. Results are presented in Appendices B and C, and although weaker, support our main findings.

[22] We also investigate whether the proportion of female All-Star analysts within a brokerage affects forecast optimism. Consistent with Jannati (2024), who documents that female All-Star analysts improve the forecasting accuracy of their non–All-Star peers through knowledge spillovers, we find that a greater presence of female All-Stars is associated with lower optimism on average. However, as detailed in Appendix F, this effect does not extend to affiliated analysts, whose optimism bias remains unchanged. This result can be interpreted in light of Bradley et al. (2012), who find that while All-Star analysts exhibit less optimism bias overall, their presence does not neutralize conflicts of interest in settings where structural pressures persist, such as hot IPO markets.

Table 10
Robustness.

Panel A: Terciles of female representation in affiliated subsample	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
Tercile2_FEM_PROP	**−0.008**	**−1.102**	**−0.006**	**−0.036****
	(−0.788)	**(−1.024)**	**(−0.384)**	**(−2.315)**
Tercile3_FEM_PROP	**−0.026****	**−2.992****	**−0.041****	**−0.061*****
	(−2.400)	**(−2.461)**	**(−2.357)**	**(−3.786)**
FEMALE	−0.026**	−3.902**	−0.013	−0.012
	(−2.030)	(−2.437)	(−0.691)	(−0.607)
Constant	0.556***	74.414***	−3.506***	−3.108***
	(2.810)	(4.422)	(−11.384)	(−9.651)
Controls included	YES	YES	YES	YES
Observations	13,810	13,810	13,810	13,810
R-squared	0.551	0.406	0.364	0.385
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Analysis of affiliation and proportion of female analysts including brokerage fixed effects	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
AFFILIATED	0.062***	5.934***	0.079***	0.069***
	(5.659)	(5.140)	(4.855)	(4.473)
FEM_PROP	0.066**	6.554**	0.004	0.028
	(2.172)	(2.215)	(0.087)	(0.693)
AFFILIATED × FEM_PROP	**−0.170****	**−10.577**	**−0.199***	**−0.215***
	(−2.185)	**(−1.269)**	**(−1.728)**	**(−1.877)**
FEMALE	−0.004	−0.709	0.005	−0.006
	(−0.714)	(−1.075)	(0.633)	(−0.734)
Constant	0.276*	48.094***	−3.647***	−3.350***
	(1.905)	(4.584)	(−15.578)	(−12.448)
Controls included	YES	YES	YES	YES
Observations	63,707	63,707	63,707	63,707
R-squared	0.482	0.311	0.296	0.347
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Brokerage FE	YES	YES	YES	YES
Panel C: Analysts that switch brokerages, using analyst-fixed effects	TP/P	TP/P_Rank	TP_NeverMet	TP_NotMetEnd
FEM_PROP	**−0.185*****	**−11.211****	**−0.309*****	**−0.199****
	(−3.723)	**(−2.358)**	**(−3.518)**	**(−2.113)**
AFFILIATED	−0.012	0.644	0.035	0.019
	(−0.490)	(0.308)	(0.993)	(0.589)
Constant	0.104	20.615	−5.099***	−4.439***
	(0.444)	(1.039)	(−12.341)	(−10.198)
Controls included	YES	YES	YES	YES
Observations	7,440	7,440	7,440	7,440
R-squared	0.595	0.504	0.408	0.433
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES

This table reports regression results from estimating Eq. (2)In Panel A we esti on the subsample of analysts that follow the same firm after switching brokerages (100 singleton observations were dropped). Panel B adds brokerage fixed effects (37 singleton observations dropped). All variables are defined in appendix A. T-statistic in parentheses. Standard errors clustered at the analyst and firm level. ***, **, and * indicate significance at the 1 %, 5 % and 10 % level, respectively.

softer self-regulation associated with gender composition. We augment Eq. (2) with the variable *SANCTIONED* (which takes the value of 1 for forecasts issued by analysts at sanctioned institutions and 0 otherwise) and with the interaction term *AFFILIATED* × *SANCTIONED*. The negative and significant coefficients of *SANCTIONED* in Table 9 show that all four optimism bias measures are on average lower at sanctioned institutions. However, the coefficients of the interaction term are either insignificant (for *TP/P* and *TP/Rank*) or positive and significant (for *TP_NeverMet* and *TP_NotMetEnd*). This supports the limited effectiveness of these sanctions in resolving conflicts of interest documented by Kadan et al. (2008), who conclude that analysts remained reluctant to issue pessimistic recommendations for their investment banking clients. Importantly for the conclusions of our analysis, the interaction between *AFFILIATED* × *FEM_PROP* remains negative and significant in this setting.

5.5. Robustness

In this section, we verify the robustness of our findings to various specifications, including the use of alternative measures for gender composition and employing different types of fixed effects.

Regarding the measures for gender composition, we use terciles of the annual percentage of women in the brokerage instead of a continuous measure. The brokerages in the bottom tercile have an average of 3.90 % female analysts, while in the middle this value is 10.82 percent and, in the top, 18.98 %. In Table 10, Panel A, the results show that target prices by analysts working for brokerages in the highest tercile of female representation are the most statistically different from those in the lowest tercile. Thus, we find that optimism bias among affiliated analysts is the lowest, both in magnitude and with the highest significance, in brokerages with the most women, consistent with high female representation being associated with the highest standard of self-regulation.[23]

While Section 5.3 addresses endogeneity concerns, our next analysis further investigates whether gender differences in the industry could stem from self-selection into brokerages with a more ethical culture by including brokerage fixed effects in the main model. We expect the gender composition within brokerages to remain relatively stable over time, meaning brokerage fixed effects may capture much of the optimism variance linked to gender composition. However, to the extent that gender composition changes from year to year, we observe a significant negative association between gender composition and optimism by affiliated analysts for all four measures, as visible in Panel B of Table 10.

Our final set of results focuses on verifying whether our findings are driven by uncontrolled analyst characteristics. Thus, we verify the robustness of our results when controlling for analyst fixed effects in the subsample of analysts who switch brokerages. Results are presented in Table 10, Panel C and support our prior conclusions.[24]

6. Conclusion

Sell-side analysts' conflicts of interest are an important issue within the financial industry since bias in sell-side research can have severe negative economic effects. Yet, regulation designed to address this issue has yielded mixed and limited results (Barniv et al., 2009; Chen and Chen, 2009; Chen et al., 2018; Corwin et al., 2017; Guan et al., 2012; Kadan et al., 2008). This could be partly due to the organizational culture of brokerages which, despite regulatory and policy efforts, encourages biased research reports to maintain investment banking clients. Improving the culture within these firms could therefore complement regulators' efforts to mitigate this type of behavior. Given the link between gender and moral reasoning (Cohen et al., 2001; Gilligan, 1993), one possible means of improving the ethical standards of financial analysts could be to increase the proportion of women in brokerages.

Our tests examine the association between gender composition and the optimism bias resulting from conflicts of interest faced by analysts working for institutions that underwrite the firms they follow. Our analysis shows that optimism bias is negatively associated with the proportion of female analysts providing research for the brokerage. This seems to result from a dynamic in which analysts contribute to the culture of their brokerage house. When brokerage mergers impose an external shock to gender composition, those analysts at brokerages experiencing an exogenous increase in female presence are less likely to exhibit bias in their equity research. Our results are robust to various specifications, including the addition of analyst and brokerage fixed effects and different measures for gender compositions in brokerages. Taken at face value, the male-dominated analyst profession could benefit from the inclusion of more women, since this would likely result in less biased research.

Our findings complement the literature on affiliated sell-side analysts' conflicts of interest and add to the literature on analyst gender, especially as we show it is the gender composition of the workforce, rather than the individual analyst's gender that has the greatest relationship with self-regulation. We believe these results will be of interest to regulators aiming to ensure the efficient flow of information in capital markets, other market participants, and certainly to brokerages making hiring decisions. We also believe these findings contribute to the discussion around working conditions in the sell-side analyst profession, showing that efforts to accommodate work-life balance to attract female employees may be beneficial to the information disseminated to markets, particularly when conflicts of interest are present.

Our study is not without limitations. We take multiple steps to establish causality and rule out the impact of endogeneity on our inferences. However, we cannot perfectly rule out self-selection of women into brokerages with a certain culture (or where a certain culture would anyway be emerging). Ultimately, our main contribution is to document that employees in brokerages with a higher proportion of women succumb to pressures induced by conflicts of interest to a lesser extent than their peers in brokerages with a lower proportion of women. In other words, the proportion of women in a brokerage indicates better self-regulation of the brokerage against conflicts of interest, a result which we believe is of interest to academics in various fields and to regulators and practitioners interested in resolving conflicts of interest.

CRediT authorship contribution statement

Andria Charalambous: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Alan Duboisée de Ricquebourg:** Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Elvira Scarlat:** Writing – review & editing, Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis. **Karin Shields:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization.

Appendix A. Variable definitions

Variable	Definition
Dependent variables	
TP/P	The target price forecast divided by the current stock price – 1. *(Sources: I/B/E/S Detail Target Price file, CRSP)*
TP/P_Rank	The rank of *TP/P*, coded from 1 to 99, within its two-digit SIC code industry in any given year where *TP/P* is defined as the target price forecast divided by the current stock price – 1. *(Sources: I/B/E/S Detail Target Price file, CRSP)*
TP_NeverMet	An indicator variable (0, 1) equal to 1 if the maximum closing price during the 12-month forecast horizon is lower than the target price forecast and 0 otherwise. *(Sources: I/B/E/S Detail Target Price file, CRSP)*
TP_NotMetEnd	An indicator variable (0, 1) equal to 1 if the actual 12-month-ahead closing stock price is lower than the target price forecast, and 0 otherwise. *(Sources: I/B/E/S Detail Target Price file, CRSP)*

(*continued on next page*)

[23] For increased robustness, we also include additional analysis in the appendix. Specifically, we repeat the estimation in model (2) using *FEM_PROP_AVE*, the average proportion of female analysts over the sample period, to better capture female presence over time. Appendix E shows that the female proportion moderates optimism bias in the presence of conflicts of interest, with significant negative results for all four coefficients. In Panel B, we find that *FEM_PROP_AVE* is negatively associated with optimism bias in affiliated brokerages, supporting its role in reducing biased research.

[24] Appendix C provides results of further analysis including analyst fixed effects (Panel A), analyst-broker fixed effects (Panel B), and quarterly fixed effects (Panel C). The direction of the main coefficient of interest, *AFFILIATED*×*FEM_PROP*, remains negative and is statistically significant in two of the four measures in the first two specifications and all measures in the third.

(*continued*)

Variable	Definition
Analyst and brokerage characteristics	
AFFILIATED	An indicator variable equal to 1 if an analyst is affiliated through either an IPO and/or SEO issue with the covering stock within a 2-year window and 0 otherwise. *(Sources: I/B/E/S Detail Target Price file, SDC)*
ALL_STAR	An indicator variable equal to 1 if an analyst was elected to the All-America Research Team by the Institutional Investor magazine in the previous year; the magazine is issued annually in October. *(Source: Institutional Investor Magazine)*
Brokerage_accuracy	The average accuracy of its analysts in a given year, where analyst accuracy is calculated as the ratio of the difference between forecasted EPS and actual EPS to stock price. (Source: I/B/E/S Detail file)
Brokerage_ALLSTAR%	The percentage of analysts holding ALLSTAR status as per the All-America Research Team in a given year. *(Source: Institutional Investor Magazine)*
Brokerage_experience	The average number of years that analysts of the brokerage have submitted forecasts in I/B/E/S. (Source: I/B/E/S Detail Target Price file)
Brokerage_size	The number of active analysts in a given year.
Brokerage_specialization	The number of industries covered by the brokerage analysts in a given year. (Source: I/B/E/S Detail Target Price file)
FEMALE	An indicator variable equal to 1 if an analyst is female and 0 otherwise. *(Sources: I/B/E/S Detail Target Price file, S&P Global Market Intelligence)*
FEM_ALLSTAR	Proportion of female analysts in the brokerage and year, who have been elected to the All-America Research Team by the Institutional Investor magazine in the previous year; the magazine is issued annually in October. *(Source: Institutional Investor Magazine)*
FEM_BROKERAGE	An indicator variable (0, 1) equal to 1 if the brokerage for which the analyst works is in the top tercile of *FEM_PROP*. *(Source: I/B/E/S Detail Target Price file)*
FEM_PROP	The percentage of female analysts making target price forecasts in a given brokerage in a given year. *(Source: I/B/E/S Detail Target Price file)*
FEM_PROP_AVE	The average percentage of female analysts making target price forecasts in a given brokerage for the years 2003-2014. *(Source: I/B/E/S Detail Target Price file)*
logBROKERSIZE	Defined as the log number of analysts employed by the investment bank in the previous year. *(Source: I/B/E/S Detail Target Price file)*
logCOVERAGE	The log number of firms an analyst has followed over the previous 12 months at the target price release date. *(Source: I/B/E/S Detail Target Price files)*
logFEXP	The log number of years an analyst has followed a specific company measured at the target price release date. *(Source: I/B/E/S Detail Target Price file)*
logGEXP	The log number of years an analyst has submitted reports to I/B/E/S measured at the target price release date. *(Source: I/B/E/S Detail Target Price files)*
SANCTIONED	An indicator variable (0, 1) equal to 1 if the investment in which the analyst is employed is one of the 12 sanctioned banks included in the Global Analyst Research Settlement. *(Source :* https://www.sec.gov/litigation/litreleases/lr18438.htm)
Firm characteristics	
INSTOWN_PCT	The percentage of quarterly institutional ownership, measured at the current quarter of the target price release date. (*Source: 13f Filings)*
LOGMV	The market value of the firm measured as the natural logarithm of market value 3 days before the target price release date, where the market value is calculated as the share price multiplied by shares outstanding. (*Source: CRSP)*
PRCMOM	The 6-month buy-and-hold return ending 3 trading days before the target price release date. (*Source: CRSP)*
STDPRC	The standard deviation of stock prices over the 12 months before the target price release date. (*Source: CRSP)*
Other controls	
MRKRET	The buy-and-hold value weighted market return over the 12-month forecast horizon following the target price release date. (*Source: CRSP)*

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2025.107484.

Data availability

Data will be made available on request.

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