CFO facial beauty and bank loan contracting

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Abstract: We examine whether facial attractiveness of borrower firms' chief financial officers (CFOs) influences bank loan contracting terms. Using a machine learning-based face beauty evaluation algorithm to measure facial attractiveness, we document that firms led by CFOs with greater facial beauty receive more favorable loan contracts from their banks, as evidenced by lower loan spreads, longer maturities, fewer covenants, and a lower likelihood of collateral requirements. We further show that the relation between CFO facial beauty and bank loan contracting terms is significantly influenced by characteristics of both the borrower and the lender. Collectively, our results suggest that loan contracting is not an entirely a rational process, as the beauty premium is at least partly driven by taste-based discrimination.

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"It's time to expose the attractiveness bias at work."

Tomas Chamorro-Premuzic (Forbes 2019)

1. Introduction

This study examines the impact of chief financial officer (CFO) facial attractiveness on bank loan contracting terms. Given that bank loans are a major source of external corporate financing (Graham et al., 2008), it is important to understand the factors that influence banks' decisions during the lending process. Whereas prior research focuses extensively on the roles of economic factors such as financial information and executive compensation structure in the lending process (e.g., Freixas and Rochet, 2008; Graham et al., 2008; Kim et al., 2011), it has paid relatively little attention to important non-economic factors such as an appearance of firms' key financial decision makers, even though such factors are likely to play an important role in face-to-face communication between the key stakeholders who negotiate debt contracts (e.g., Mulford et al., 1998).[2]

A few studies investigate whether borrowers' facial appearance impacts peer-to-peer lending decisions (e.g., Pope and Sydnor, 2011; Duarte et al., 2012; Ravina 2019). Whereas peer-to-peer lending is primarily conducted via online platforms and involves smaller loans, a unique feature of the bank lending market is that one important way for the loan officer to gather soft information is through face-to-face interactions with a potential borrower (Berger et al., 2005). Rather than making lending decisions based purely on hard information which can easily be summarized in a report, physical interactions with CFOs help loan officers to acquire proprietary firm-specific information that may be unavailable to non-lenders. Accordingly, the facial attributes

[2] Our discussions with bankers about their experiences with CFOs during face-to-face negotiations, suggest that visual appearance sets the tone and direction of the loan negotiations.

of CFOs could significantly influence the outcome of loan contracts. It is unclear, however, whether facial attributes will necessarily have an incremental effect over firms' economic fundamentals, because banks are sophisticated lenders for which any bias in decision-making can be costly (Becker, 1971; Ashenfelter and Rees, 1973).

Our study is the first to investigate whether the facial attractiveness of a firm's CFO plays a role in bank loan contracting, and if so, how it influences bank loan cost and structure. We focus on CFOs because they play a pivotal role in firms' financial decisions, including negotiating the terms and conditions of bank loan contracts (Francis et al., 2013). Banks acquire essential information that is important to establish the terms of the loan contract from firm management (normally CFOs) through private communications such as on-site meetings and phone calls.[3] Accordingly, CFOs' participation in the lending process shapes loan contracting terms.

We focus on facial attractiveness, one of the three key dimensions of inferred personality traits based on facial impressions, because facial attractiveness is of pervasive interest (Scholz and Sicinski, 2015)[4] and therefore likely to influence lenders' attention and communication between CFOs and lenders. Together with trustworthiness and competence,[5] these three factors (traits) capture about three quarters of the variation in people's first impressions (Oosterhof and Todorov, 2008; Sutherland et al., 2013). Trustworthiness reflects the observer's perceptions about the individual's ability, benevolence, and integrity (Hsieh et al., 2020); competence concerns perceptions about the individual's ability to carry out their intentions (Oosterhof and Todorov, 2008); and attractiveness is associated with perceived novelty, initial attraction, and greater

[3] https://corporatefinanceinstitute.com/resources/careers/designations/ceo-vs-cfo/

[4] For example, revenue of the U.S. cosmetic industry is estimated to amount to about 49.2 billion U.S. dollars in 2019. https://www.statista.com/statistics/243742/revenue-of-the-cosmetic-industry-in-the-us/

[5] Peng et al. (2022) use competence and dominance interchangeably.

attention from the information bearers (Peng et al., 2022). Although the three face factors are based on human perceivers' first impressions, trustworthiness and competence have a more persistent effect (Peng et al., 2022). Attractiveness, on the other hand, is transient because novelty eventually wears off (Sutherland et al., 2013). In other words, the "beauty bias" is likely to be driven by initial taste-based discrimination rather than by statistical discrimination.[6]

Because loan negotiations involve frequent face-to-face interactions between the bank(er) and the CFO, the CFO's facial attractiveness during initial and subsequent interactions is likely to play a significant role in establishing the initial relationship between the two parties, which in turn influences the negotiations' outcome. We conjecture that attractive CFOs may enjoy short-lived benefits arising from the beauty bias. Specifically, because people are more inclined to communicate and cooperate with more facially attractive individuals (Mulford et al., 1998), more attractive CFOs are likely to have longer face-to-face interactions with the lending officers and are thus able to deliver more favorable value-relevant information during these interactions. Correspondingly, we expect that high facial attractiveness reduces lenders' information uncertainty through the parties' face-to-face interactions, which should manifest in lower lending spreads and more favorable loan terms. In addition, the lending officers could consciously or subconsciously develop beliefs that attractive individuals will deliver better performance (Scholz and Sicinski, 2015) and offer more favorable loan terms to the borrowers with attractive CFOs. However, it is not clear that this impact will necessarily be incrementally important over firms' economic fundamentals. Given that bank lenders are sophisticated financial players, as such,

[6] Taste-based discrimination and statistical discrimination are two leading theoretical explanations for labor market discrimination. Taste-based discrimination is essentially prejudice, where, for example, a Caucasian hiring manager who dislikes Asian people might hire an inferior white candidate instead of a better qualified Asian applicant. Statistical discrimination, on the other hand, is a theorized behavior (i.e., Caucasian may on average have higher productivity), not a blanket dislike for people of a certain race.

differences in facial attractiveness may not play a significant role in the lending process. This could be due to the lender's analytical skills, such as modeling techniques and other cognitive abilities that may dominate the cognitive bias of physical attractiveness, or could be because discrimination may be costly to the firm and could be driven out by market competition (a null hypothesis).

To test our conjecture, we download pictures of CFOs from Google and use a machine-learning algorithm to construct a facial-beauty database for US CFOs for the sample period 2006 to 2016. We conduct a validity check via Amazon Mechanical Turk (MTURK, https://www.mturk.com/) to confirm that our computer-based facial attractiveness measure is a valid and reliable measure of human assessments of facial beauty and that people are more willing to cooperate with individuals (i.e., CFOs) with higher facial attractiveness.

We document several important results. First, we find a strong negative relation between CFO facial beauty and bank loan cost. Depending on the model specification, the reduction in loan spread is economically significant (14–39 basis points) relative to the sample average spread of 183 basis points (bps) over LIBOR, where a one standard deviation increase in facial beauty is associated with a reduction in loan spread of 7–19 bps. We verify that our results hold after controlling for potential endogeneity related to the difficulty of separating the influence of entity and individual effects using first-differences analysis around CFO turnovers, controlling for other CFO facial characteristics (i.e., trustworthiness and competence) and the facial attractiveness of chief executive officers (CEOs), and using alternative specifications and additional controls.

Second, we conduct cross-sectional analyses to explore the potential channels through which CFO beauty influences bank loan contracting. We expect that soft information, and therefore face-to-face interactions between CFOs and bankers are more important for smaller and younger firms and firms with limited credit information. Consistent with our expectation, we document that the impact of CFO facial attractiveness on the cost of bank loans is greater for smaller and younger firms and for firms with no credit rating. We also find a stronger impact of CFO facial attractiveness on the cost of bank loans when the CFO borrows from the lender for the first time, and that repeated interactions (i.e., CFO tenure) weaken the impact. These findings reinforce that CFOs with higher facial attractiveness enjoy greater initial benefits and the novelty of facial attractiveness eventually wears off (Peng et al., 2022).

We also examine how the relation between CFO facial attractiveness and bank loan contracting varies with lender characteristics. We expect that face-to-face interactions are less important for larger banks because they rely less on the soft information that is typically available through personal interactions (Berger et al., 2005), for lenders that have a prior banking relationship with the borrowers (i.e., the CFO's firm) because information frictions are reduced through repeated interactions (Petersen and Rajan, 1994), and for relationships with greater geographical distance between the borrower and the lender which makes face-to-face meetings less likely (Hollander and Verriest, 2016). We also expect the beauty premium resulting from the behavioral bias of lenders to be lower in a more competitive market because the increased pressure on bank employees to pursue profits will attenuate the taste-based facial discrimination (Becker, 1971).[7] Consistent with our conjecture, we find that the negative association between CFO facial attractiveness and the cost of bank loans is weaker for larger banks, banks that have dealt with the firm in the past, banks located further away from the borrower, and banks that operate in a more competitive environment.

[7] Economic theories suggest that taste-based discriminations could be completely eliminated, whereas statistical discriminations could not.

These cross-sectional test results confirm the mechanism through which CFO facial attractiveness influences information transfer (communication) between firms and lenders, and indicate that the attractiveness premium produces short-lived economic effects and is primarily driven by taste-based discrimination. Next, we examine whether CFO facial beauty influences loan contract terms other than loan spread. We find that loans contracted by banks with more attractive CFOs have longer maturity, fewer covenants, and are less likely to require collateral. These more lenient non-price contract terms potentially lead to debt cost savings and foster other benefits such as lower transaction costs from less frequent debt financing, thus enabling the firm to take advantage of greater numbers of profitable investment opportunities.

Lastly, we investigate an alternative explanation for the observed negative association between CFO facial beauty and bank loan costs, i.e., whether CFO facial attractiveness is associated with omitted variables, such as managerial ability and default probability. We do so by analyzing a subset of firms with bond yields, utilizing the fact that banks have closer interactions with CFOs than with bond holders. Our results indicate a larger impact of CFO facial attractiveness on bank loan rates than on bond yields. This result suggests that the beauty premium in bank loan contracting is likely driven by taste-based discrimination, i.e., by lenders' cognitive bias in dealing with individuals with facial attractiveness, rather than by an omitted variable, or by statistical discrimination, i.e., by lenders' use of CFO beauty as a predictor of default risk.

Our study makes several important contributions to the literature. First, we contribute to the literature on determinants of bank loan contracting by documenting that non-economic factors influence bank loan contracting outcomes. We demonstrate that CFOs' facial beauty has a statistically and economically significant impact on loan costs and features. Second, our evidence indicates that facial attractiveness affects the interactions between CFOs and bank officers, and the strength of these interactions varies with both borrowing firm and CFO characteristics (i.e., firm size, age, and CFOs' prior interactions with the bank), and with lender characteristics (i.e., bank size, competitive environment, and geographical distance). Thus, our results also shed light on the social nature of the interactions between CFOs and their lenders during the negotiation process, which manifest the debt-contracting value of CFOs during the negotiation process with banks (Li et al., 2023). Third, although recent studies show mixed evidence on whether borrowers' facial attractiveness impacts peer-to-peer lending decisions (e.g., Pope and Sydnor, 2011; Duarte et al., 2012; Ravina, 2019), we know relatively little about whether facial beauty influences bank lending decisions. Our study contributes to this investigation by providing evidence that CFO facial attractiveness plays an important role in bank loan contracting. Lastly, we investigate the implications for bond spreads and future default probabilities of the facial attractiveness of firms' CFOs, and thus explore whether discrimination on CFOs' attractiveness is taste-based or statistical. We document that CFO facial beauty is not related to bond spreads or actual default probabilities, and that the impact of facial attractiveness is mainly driven by taste-based discrimination that is costly to the economy (Becker, 1971). Our results therefore offer important insights about the impact of cognitive biases in a debt contracting setting, and therefore have important implications for regulators and practitioners.

The remainder of this paper proceeds as follows. Section 2 reviews the prior research and develops our hypotheses. Section 3 discusses the methodology used and the research design. Section 4 presents the main empirical findings and section 5 provides additional test results. Section 6 concludes the paper.

2. Related literature and hypotheses development

The research questions of whether and how CFO facial beauty is related to bank loan cost are associated with two streams of literature: literature on facial features (and particularly facial attractiveness) and literature on bank loan contracting. We discuss each of these streams of literature in this section and then develop this study's hypotheses.

2.1. Literature on facial features and attractiveness

The beauty bias, also known as the "beauty premium," is a well-documented phenomenon in the fields of sociology, psychology, and economics (Jackson et al., 1995; Hosoda et al., 2006; Mobius and Rosenblat, 2006; Graham et al., 2017), whereby people are more inclined to communicate and cooperate with facially attractive individuals (Mulford et al., 1998) and that attractive individuals are perceived to be smarter, more successful, more important, and more valuable than other individuals (Umberson and Hughes, 1987; Feingold, 1992; Houston and Bull, 1994; Eckel and Petrie, 2011).[8] Recent research in accounting and finance provides further evidence that this cognitive bias has a significant impact on performance in various areas of capital markets, where, for example, individuals with higher facial beauty (attractiveness)[9] receive higher remuneration (Hamermesh and Biddle, 1994; Li et al., 2021), raise more charity donations (Landry et al., 2006), have better access to private information (Cao et al., 2020; Li et al., 2020), and receive more favorable treatment from lenders in personal loan transactions (Ravina, 2019).

[8] For example, prior studies have examined the relations between physical appearance and various career and corporate outcomes (e.g., Jackson et al., 1995; Hosoda et al., 2006; Mobius and Rosenblat, 2006; Graham et al., 2017) and documented that there is systematic discrimination against individuals with low facial attractiveness in settings such as the hiring process (Ruffle and Shtudiner, 2015), job promotion (Morrow et al., 1990), performance negotiation (Haselhuhn et al., 2014), forecasting performance (Cao et al., 2020), and lending transactions (Duarte et al., 2012).

[9] We use facial attractiveness and beauty interchangeably in this paper.

The importance of facial beauty has been acknowledged by many studies in psychology and economics, which have found not only that the "beauty premium" often has a greater impact on social outcomes than other variables, but that it also has a practical significance for various corporate outcomes (Hamermesh and Biddle, 1994; Langlois et al., 2000; Li et al., 2021; Peng et al., 2022). Ceteris paribus, attractive people are judged and rewarded more favorably than unattractive people, partly due to the social stereotypes associated with beauty (Dion et al., 1972; Eagly et al., 1991) and partly due to people's greater willingness to interact with physically attractive individuals (Hamermesh and Biddle, 1994; Mulford et al., 1998).[10]

Since the development of physical attractiveness stereotype theory by Dion et al. (1972), which predicts that individuals draw inferences about others based on knowledge of the categories to which they belong, early studies have shown that higher attractiveness contributes to the belief that a person is smarter, more successful, and more valuable (Cialdini, 1984), and correlates with measures of achievement, mood, and well-being (Umberson and Hughes, 1987). Furthermore, people are more likely to have interactions with physically attractive individuals (Feingold, 1992) and to share personal information with them (Brundage et al., 1976). More recent studies document the positive effects of CEO facial attractiveness on stock returns around job announcements, earnings announcements, and acquisition announcements (Halford and Hsu, 2020), on employee and CEO compensation (Mobius and Rosenblat, 2006; Graham et al., 2017; Li et al., 2021), and on revenue in the advertising industry (Pfann et al., 2000).

[10] Prior literature documents that many effects of attractiveness are independent of gender (Dion et al., 1972; Eagly et al., 1991; Hamermesh and Biddle, 1994), where an individual's beauty is a status characteristic, similar to sex and age, independently of any sexual or romantic appeal (Webster and Driskell, 1983).

2.2. Literature on bank loan contracting and other lending markets

The main tasks of bank officers who negotiate the terms of lending contracts with firms' CFOs include collecting information, understanding borrowers' operating and financial conditions, and evaluating borrowers' repayment abilities (Ball et al., 2008; 2015). In addition to hard information provided by firms (e.g., financial records), soft information obtained during the negotiation process helps facilitate cooperation between the parties, affects various aspects of financial contracts, and provides lenders with additional information that is useful in making decisions.[11] The existing literature verifies the role of implicit soft information in bank loan contracting and provides convincing evidence on the use of soft information in screening borrowers, showing that it is helpful in alleviating information asymmetry (Diamond, 1989; Petersen and Rajan, 1994; Agarwal and Ben-David, 2018). For example, Bozanic et al. (2018) measure credit-risk-relevant soft information using linguistic uncertainty and provide strong evidence that soft information is relevant to the assessment of borrowers' credit risk and affects bank loan contract terms.

How commercial banks obtain and process soft information is an important question to explore (Campbell et al., 2019); however, few researchers have examined the role of soft information in loan contracting. We fill this gap by providing insights about the communication of soft information through personal interactions in the bank loan contracting setting.

A few studies investigate whether borrowers' facial appearance impacts peer-to-peer lending decisions, but find mixed evidence (e.g., Pope and Sydnor, 2011; Duarte et al., 2012; Ravina, 2019). Whereas peer-to-peer lending is primarily arranged via online platforms and

[11] Liberti and Petersen (2019) categorize information into hard information and soft information based on its quantifiability, storability, verifiability, and objectivity of assessment.

involves smaller loans and individual borrowers,[12] in bank lending an important way for the loan officer to gather soft information is through face-to-face interactions with the potential borrower (Berger et al., 2005). However, because bank lenders are sophisticated financial players who may rely mainly on hard skills, such as modeling techniques and other cognitive abilities, facial attractiveness may not play a significant role in the lending process. We contribute to the literature by providing evidence on how clients' facial attractiveness impacts sophisticated lenders.

2.3. Hypotheses development

Credit risk is the most important risk faced by banks and the most important determinant of loan pricing (Freixas and Rochet, 2008). It consists of two elements: default risk and information risk (Duffie and Lando, 2001). Bankers often arrange physical meetings with their clients to assess what are commonly called the Five Cs of credit risks: "Character, Capacity, Capital, Collateral, and Conditions," which helps the lender determine the level of risk associated with providing the borrower with the requested funds (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Banerjee, 2019). Construction of bank loan arrangements is largely based on historical financial reporting information and financial forecasts (Ball et al., 2008; Graham et al., 2008; Wittenberg-Moerman, 2008; Carrizosa and Ryan, 2017). In addition, lenders acquire soft information (e.g., about the character of the firm's management) through interpersonal interactions to factor into their lending models. Such soft information is often used to supplement hard financial information (Beaulieu, 1996; Francis et al., 2013; Fogel et al., 2018).

[12] For example, Ravina (2019) analyzes a sample of applications and loans from Prosper.com, a US online lending platform, where borrowers posted 37,897 loan applications (10% of which were funded, with loans ranging from $1,000 to $25,000) and where the largest total amount lent by a single individual was $738,488.

Prior literature documents that among senior management, executive officers with financial expertise exert the most direct influence on financial policies and related strategies (Mian, 2001; Geiger and North, 2006; Ge et al., 2011). In particular, CFOs play an important role in corporate finance decisions and choices of debt structure because they possess specialized financial knowledge (Chava and Purnanandam, 2010; Gore et al., 2011). In a survey of CFOs, Servaes and Tufano (2006) find that specific finance activities that CFOs view as relatively important include maintaining relationships with banks and debt issuance and management. For a large bank loan, the CFO is therefore the person most likely to be responsible for directly negotiating with banks and influencing the final loan contract terms.

Given the documented widespread existence of the beauty premium in the labor market, we conjecture that CFOs' facial attractiveness likely affects loan officers (intentionally or unintentionally), and therefore affects the outcome of bank loan contracting. Prior literature documents that facial attractiveness is associated with more favorable judgement in a variety of settings. Overall, prior evidence suggests that there are two possible channels through which the "beauty premium" manifests.

First, people prefer to work with attractive individuals in a work environment because of cognitive bias.[13] For example, Mulford et al. (1998) find that people are more willing to cooperate with individuals they find more attractive. Accordingly, we postulate that facial beauty is related to lower perceived information risk, as bank officers are more likely to grant attractive CFOs time and opportunity to communicate relevant information, which leads to lower information risk and

[13] It is also possible that physically attractive individuals are more confident and have better communication and social skills (Feingold, 1992; Mobius and Rosenblat, 2006; Scholz and Sicinski, 2015). Empirically, it is almost impossible to distinguish "beauty has skills" and "beauty as taste" because both predict a preference for interactions with more attractive individuals. In our setting, however, we believe it is unlikely that CFOs with facial attractiveness are significantly more confident than CFOs without facial attractiveness because individuals go through a lot of training and hurdles before becoming a CFO of a large publicly traded company.

thus lower risk premium for the loan. In other words, the exchange of information may shrink the variance of lenders estimation of future cash flow (i.e., reduce information risk).[14] In addition, the loan officer could subconsciously offer more favorable loan terms to the attractive CFO. The first channel suggests that beauty is a "medium" (i.e., it facilitates information transfer). Beauty as a "medium" is a form of taste-based discrimination (Becker, 1971) and is a result of a cognitive bias.

Second, attractive individuals are often viewed as more capable, as documented for physically attractive individuals by Mobius and Rosenblat (2006). In this case, bankers may use CFO facial attractiveness as a signal, for example about future repayment ability (Ravina, 2019), because they have imperfect information about individuals they interact with. That is, facial attractiveness could be correlated with repayment ability and the lenders are using this correlation in the underwriting process. The second channel suggests that beauty is "content", which is often labeled as statistical discrimination, because it could be the result of a rational decision (Arrow, 1973). The above arguments lead to our first hypothesis, stated in alternative form:

> **H1:** *Ceteris paribus, banks charge a lower loan cost to borrowers whose CFOs have higher facial beauty*.

There are several factors that could affect the relation between facial attractiveness and bank loan costs, and these moderating factors help us to distinguish whether this relation is mainly driven by taste-based discrimination or statistical discrimination.

First, we postulate that the borrowing firm's and its CFO's characteristics impact the importance of soft information during the underwriting process. From the firm's perspective, we expect soft information to be more important for smaller and younger firms that are less established

[14] We acknowledge that higher transparency on poor fundamentals could also increase loan price. In other words, there is a mean effect. However, we believe that if anything, this only applies to a very small set of firms that are heavily financially distressed. We address this possibility in one of our cross-sectional analyses that examines the impact of CFO facial attractiveness among firms with high credit risks.

and for which there is less hard public information available (Liberti and Petersen, 2019). Similarly, soft information may be more important for firms with no credit ratings, as lenders cannot rely on ratings and credit reports produced by credit rating agencies. From the CFO's perspective, although lenders experience information asymmetry during the underwriting process, a richer set of information accumulated via previous interactions with a borrower (i.e., the CFO) may provide additional useful information for lenders to evaluate the borrower's fundamentals. These information sources may help lenders evaluate management integrity and default risks. When CFOs have longer tenure, lenders accumulate more specific and detailed information about them. Face-to-face interactions may therefore be less important for lenders that have a prior banking relationship with the CFO because information friction is reduced through repeated interaction between the lender and the CFO. Accordingly, we expect that face-to-face interactions are less important if the CFO borrowed from the lender in the past either in his/her current position or in a previous position. Drawing on the above discussion, we therefore propose our second set of hypotheses, stated in alternative form:

> **H2a:** *Ceteris paribus, borrowers' information availability weakens the negative association between CFO facial attractiveness and cost of bank loans.*
>
> **H2b:** *Ceteris paribus, prior interactions between the CFO and the bank weaken the negative association between CFO facial attractiveness and cost of bank loans.*

Second, the impact of CFO facial beauty on bank loan contracts could also be affected by the lender's characteristics. Prior studies suggest that larger banks make lending decisions primarily based on hard information, whereas smaller banks rely more on soft information (Berger et al., 2005). This suggests that interactions with CFOs are more important for smaller banks, and therefore CFO facial attractiveness should play a more important role in such lending relationships. Hence, we predict that bank size moderates the negative relationship between CFO facial beauty and loan cost. Furthermore, prior studies suggest that discrimination based on taste (e.g., preference for dealing with facially attractive individuals) is costly and ultimately undermines competitiveness (Becker, 1971; Ashenfelter and Rees, 1973). The competitiveness of the lending market should therefore attenuate the impact of CFO facial attractiveness because pressure on bank employees to pursue profits should diminish the beauty effect. Finally, we also expect that a previous lending relationship between the borrower (i.e., the firm) and the lender diminishes the effect of facial beauty on loan pricing, because lenders may accumulate adequate hard information about the borrower firm, and therefore rely less on the CFO's appearance. Finally, we expect that the distance between the borrower and the lender will impact the role of CFO facial attractiveness (Berger et al., 2005) because longer distances between borrower and lender make face-to-face meetings less probable and less frequent, which decreases the importance of face-to-face interactions. Therefore, we expect the negative relation between facial attractiveness and loan costs to weaken as the distance between the borrower and the lender increases. We formulate our third set of hypotheses, stated in alternative form, as follows:

> **H3a:** *Ceteris paribus, banks' size weakens the negative association between CFO facial attractiveness and cost of bank loans.*

> **H3b:** *Ceteris paribus, banks' competitive environment weakens the negative association between CFO facial attractiveness and cost of bank loans.*

> **H3c:** *Ceteris paribus, bank's prior relationship with the borrower weakens the negative association between CFO facial attractiveness and cost of bank loans.*

> **H3d:** *Ceteris paribus, banks' geographical distance from the borrower weakens the negative association between CFO facial attractiveness and cost of bank loans.*

Lastly, if CFOs with high facial attractiveness have better opportunities to convey information about a company's future prospects, lenders might incorporate this information into bank loan contracts by altering not only the lending rate but also other contract terms. We therefore follow Graham et al. (2008) and focus on how CFO facial attractiveness impacts the three major non-price debt contract features: collateral, loan maturity, and total number of covenants. Prior literature shows that lenders are more likely to request collateral, shorten loan duration, and increase the number of covenants for loans to borrowers with high information uncertainty (Demiroglu and James, 2010; Kim et al., 2011). If lending officers have more frequent physical interactions with CFOs with higher facial attractiveness, lenders are likely to obtain more soft information from these interactions, and therefore we expect banks to be willing to accept less collateral from, grant longer maturity loans to, and impose fewer covenants on borrowers whose CFOs are more attractive. This leads to our final hypothesis, stated in alternative form as:

> **H4:** *Ceteris paribus, banks accept less collateral from, grant longer duration loans to, and impose fewer covenants on borrowers with more attractive CFOs.*

3. Methodology

3.1 Measure of facial beauty and external validation

Although many prior studies use measures of beauty based on human ratings (e.g., Mulford et al., 1998; Eckel and Petrie, 2011; Graham et al., 2017), recent studies use machine learning-based facial-feature evaluation (e.g., Bi et al., 2020; Peng et al., 2022). In this study, we follow the latest literature and use a computer-based facial attractiveness measure, which facilitates data availability and the objectivity and replicability of the measure. We assess CFO facial beauty using a machine learning method (described in detail in Appendix 1) and conduct a validity check with human assessors to confirm that our computer-based measure of facial attractiveness is a valid and reliable proxy for human assessments of facial beauty (described in detail in Appendix 2).

Although beauty is a subjective assessment, we believe that the use of machine learning-based technology is appropriate in the bank loan contracting setting for the following reasons. First, machine learning-based facial-feature evaluation techniques are well developed in the field of computer science (e.g., Dalal and Triggs, 2005; Eisenthal et al., 2005; Liang et al., 2018) and have been widely used in the recent literature (e.g., Bi et al., 2020; Hsieh et al., 2020; Peng et al., 2022).[15] Second, machine learning-based technology is efficient and cost-effective for analyzing large samples, is more objective in that it is not sensitive to individual judgements and biases, and it allows researchers to replicate previous findings.

3.2. Sample and other data

Following previous literature (e.g., Graham et al., 2008), we measure loan spread by the amount the borrower pays (in bps) over the London Interbank Offered Rate (LIBOR) for each dollar drawn, as LIBOR is often used as a benchmark rate in financial contracts, such as interest rate derivatives, adjustable-rate mortgages, and corporate loans (Duffie and Stein, 2015). We obtain companies' financial statement data from Compustat and bank loan data from Reuters-DealScan. We merge the loan data and the financial data using the Gvkey and facility link table provided by Chava and Roberts (2008). Following previous studies (e.g., Graham et al., 2008), we conduct our analysis at the facility level; in other words, we treat each loan contract as an independent observation. Our final sample comprises 5,271 unique loans for 1,093 publicly traded US firms. Table 1 illustrates the sample selection process.

[Insert Table 1 about here]

3.3. Research design

We employ the following regression model to test H1:

$$Loan\ Spread_{it} = \beta_0 + \beta_1 CFO\ Beauty_{it} + Controls + Firm\ FE + Year\ FE + \mu_{it}\,, \qquad (1)$$

[15] A machine learning-based facial-feature evaluation technique is feasible because some particular facial characteristics associated with beauty can be detected using machine-based technology (Eisenthal et al., 2005).

where *i* denotes the firm and *t* denotes the year. *Loan Spread* measures the loan cost and denotes the amount the borrower pays in basis points over LIBOR. We use this measure because it is the most directly observable outcome variable.[16] Our variable of interest is *CFO Beauty*, a time-invariant continuous measure of CFO facial beauty, where 1 denotes the lowest level of beauty and 5 denotes the highest. As discussed in section 2, we expect the coefficient on this variable (β_1) to be negative.

We control for several client and loan characteristics that may influence the loan cost. Specifically, we control for client size (*Size*), profitability (*ROA*), leverage (*Leverage*), operational risk (*Operational Risk*), asset tangibility (*Tangibility*), market-to-book ratio (*MB*), financial health status (*Altman Z*), loan size (*Loan Size*), and the duration of the loan (*Loan Maturity*). We also control for CFO age (*CFO Age*) and gender (*CFO Gender*). To control for possible differences across firms and years, we also add firm and year fixed effects to our model. All standard errors are clustered at the firm level to mitigate autocorrelation concerns. Appendix 3 provides detailed definitions of all variables.

Our second set of hypotheses predicts that both borrower and CFO characteristics affect the relation between bank loan cost and CFO facial beauty. To test H2a, we examine whether CFO facial beauty is less important for larger firms (*Firm Size*), older firms (*Firm Age*), and firms that have their loans rated (*Rated*), all of which are associated with reduced default risk (Bharath et al., 2008). To test H2b, we utilize three proxies for prior relationships between the CFO and the bank: (1) the number of years the CFO has been in office (*CFO tenure*), (2) whether the CFO borrowed

[16] We also use the natural logarithm of *Loan Spread* and our results remain the same (results not tabulated and are available upon request).

from the bank while working at the firm in the past (*Prior Loan*), and (3) whether the CFO dealt with the lender at a prior workplace (*Prior CFO*).

Our third set of hypotheses predicts that lender characteristics affect the relation between bank loan cost and CFO facial beauty. To test H3a–3d, we investigate whether bank size (*Large Bank*), bank competitive forces (*Bank Competition*), previous relationship between the borrower and the lender before the CFO's tenure (*Prior Bank*), and geographic distance between the bank's headquarters and the client's headquarters (*Distance*) affect the relation posited in our first hypothesis.

4. Results

4.1. Summary statistics

We report summary statistics for all variables used in the main analysis in Table 2. *CFO Beauty* has a mean value of 2.834, which is slightly lower than the mean value of 2.990 in our training dataset.[17] The standard deviation of 0.486 suggests that our sample has a similar distribution to the training dataset (standard deviation of 0.491).[18]

Table 2 also reports descriptive statistics for client firm characteristics and loan characteristics. Our main dependent variable, *Loan Spread*, has a mean (median) value of approximately 183 (150) bps and a standard deviation of 114. The loans in our sample have a mean (median) size of approximately \$393 million (\$400 million) and a mean (median) maturity of approximately 47 (61) months. Approximately 40% of the loans in the sample are secured by

[17] Please see Appendix 1 for details about the training sample.

[18] Although theory suggests that individuals with higher facial beauty have comparative advantages in career advancement (e.g., Landy and Sigall, 1974), CFO beauty in our sample has a mean value of 2.838, which is slightly lower than the mean value of 2.990 in the training dataset. The difference between the means of the two samples is small and not statistically significant and could be due to a number of demographic differences (e.g., age) between the two samples.

collateral. Firms in our sample have mean total assets of $5.53 billion, return on assets of 12.10%, leverage of 29.70%, market-to-book ratio of 2.87, operational risk ratio of 4.00%, asset tangibility ratio of 48.20%, and Altman Z-score of 3.121. CFOs in our sample have a mean age of approximately 51 and about 90% are male.

[Insert Table 2 about here]

Table 3 reports Pearson correlations. CFO beauty is negatively and statistically significantly related to loan spread, the likelihood the loan is secured, and the number of covenants.

[Insert Table 3 about here]

4.2. Relation between CFO facial attractiveness and loan costs

Table 4 presents the estimation results for model (1), relating loan spread to CFO beauty. Column (1) in Table 4 shows that *CFO Beauty* is negatively and statistically significantly related to loan spread (–38.745, t-stat. = –12.12). When we include all controls and industry and year fixed effects in the model (column (2)), we obtain a negative and significant (at the 1% level) coefficient on *CFO Beauty* (coefficient = –19.319, t-stat. = –4.53). We find consistent results in column (3), when we control for firm and year fixed effects (coefficient = –14.306, t-stat = –2.79).[19] These results are consistent with Hypothesis 1 and indicate that CFO facial beauty and bank loan spread are reliably negatively related. The results show that a one standard deviation increase in *CFO Beauty*

[19] Controlling for firm fixed effects could eliminate the impact of time-invariant but firm-specific variables, such as the location of firm headquarters, that may influence both the CFO's facial attractiveness and bank loan costs. In other words, firm fixed effects allow us to examine the impact on bank loans when a firm is managed by a CFO with facial attractiveness versus without facial attractiveness. We therefore use firm fixed effects in all other models.

is associated with a reduction in loan spread of approximately 6.95 bps (column 3), which is economically meaningful.[20]

Regarding the control variables, consistent with prior literature, we find that firms with larger size, greater profitability, more tangible assets, better financial health, and male CFOs have statistically significantly lower loan spreads. Conversely, loan spreads are statistically significantly higher for firms with higher leverage and higher operational risk.

[Insert Table 4 about here]

4.3. Cross-sectional differences in the relation between CFO attractiveness and loan costs

We next examine cross-sectional variation in the relation between CFO facial attractiveness and bank loan costs. First, we examine how this relation varies with borrowers' information environment. H2a predicts that the interactions between CFOs and lenders (and, therefore, soft information) are less important for bigger and older firms that are more established and for which there is more hard information publicly available (Liberti and Petersen, 2019). Accordingly, we predict positive coefficients on the interaction terms *CFO Beauty* × *Firm Size*, *CFO Beauty* × *Firm Age*, and *CFO Beauty* × *Rated*. Columns (1) to (3) of Table 5 show the impact of individual components of borrower's characteristics on loan spread, whereas column (4) reports a combined model. Consistent with H2a, the positive and significant interaction coefficients indicate that CFO beauty is less important during loan negotiations between banks and large and established firms that have their debt rated by credit rating agencies. The coefficient of the interaction term *CFO Beauty* × *Rated* is of particular importance as it suggests that CFO facial attractiveness plays a

[20] The magnitude of the effect is comparable to that of other major economic factors. For example, Kim et al. (2011) report that a one standard deviation increase for internal control weakness is accompanied by a 9.4 basis point increase in loan spread.

bigger role for firms with higher credit risk. In other words, this evidence suggests that it is unlikely that higher transparency on poor fundamentals increases loan price.

[Insert Table 5 about here]

H2b predicts that prior interactions weaken the negative association between the cost of bank loans and CFO facial attractiveness because financial institutions have had more opportunities to communicate with the CFO in the past, and thus the impact of CFO beauty on loan pricing is expected to be reduced. Therefore, we predict positive coefficients on the interaction terms *CFO Beauty* × *CFO Tenure*, *CFO Beauty* × *Prior Loan*, and *CFO Beauty* × *Prior CFO*. Columns (1) to (3) of Table 5 present the results of our second hypothesis. Consistent with the main results reported in Table 4, the main effect of CFO beauty (captured by the coefficient on *CFO Beauty*) is negative and statistically significant in all specifications. More importantly, the coefficients on all three interaction variables are positive and statistically significant. Column (4) reports a combined model with all three proxies for prior interactions between the CFO and the bank, and the results are consistent with those in columns (1) to (3). Collectively, these findings support H2b, that the impact of CFO beauty on loan costs is more pronounced when the CFO deals with the bank for the first time. In other words, we provide evidence that the effect of facial attractiveness is short-lived, i.e., CFO beauty has a smaller impact on the communication of information to lenders when there are repeated face-to-face interactions.

[Insert Table 6 about here]

The third set of hypotheses predicts that the effect of CFO facial beauty on bank loan costs is affected by the lender's characteristics (i.e., bank size, competitive environment, prior relationship with the firm, and geographical distance between lender and borrower). Columns (1) to (4) of Table 7 present the results of our tests of Hypotheses 3a–3d. Consistent with the results in Table 4, the main effect of CFO beauty (captured by the coefficient on *CFO Beauty*) is negative and statistically significant in all specifications. The coefficients on the interaction variables of interest are all positive and statistically significant at conventional levels. Column (5) reports a combined model with all the interaction variables and shows that the reduced effect of facial beauty on loan cost is most pronounced for large banks and banks that operate in a more competitive environment.[21] These findings indicate that large bank lenders rely less on face-to-face interactions in the due diligence process, and that the beauty premium is a form of taste-based discrimination that can be costly to the bank and is attenuated by market competition.

[Insert Table 7 about here]

4.4. Relation between CFO facial attractiveness and other loan features

In addition to loan spread, lenders use non-price terms in loan contracts to mitigate information problems. Prior literature shows that lenders are more likely to request collateral from borrowers with high information uncertainty, and to decrease loan duration and increase the number of covenants (Graham et al., 2008; Chan et al., 2013; Demerjian, 2017). Because lending officers and CFOs with higher facial attractiveness are expected to interact more frequently, lenders are more likely to obtain soft information from borrowers, which in turn will attenuate the information uncertainty. Accordingly, we expect that in loan contracts with borrowers whose CFOs are more attractive, banks will require less collateral (*Secured*), grant longer maturity loans (*Loan Maturity*), and include fewer covenants (*# Covenants*). We test the impact of CFO beauty on these features in this subsection.

[21] As a robustness check, we repeat these tests controlling for other loan contract terms, including the number of covenants, collateral requirements, and the number of lenders in the loan syndicate. We find that all the coefficients of interest retain their sign and are statistically significant.

Column (1) of Table 8 shows that firms with higher CFO beauty are statistically significantly less likely to be required to provide collateral when obtaining a loan (coefficient = –0.052, t-stat. = –2.45), supporting the argument that banks offer more favorable loan terms to firms with more attractive CFOs. This result is consistent with prior literature that finds banks use collateral requirements to mitigate potential default risk (Graham et al., 2008). Column (2) of Table 8 shows that firms with more attractive CFOs obtain loans that have longer maturity, and the effect is significant at the 10% level (coefficient = 0.057, t-stat. = 1.68), supporting the conjecture that banks offer more favorable loan terms to firms that have more attractive CFOs. This finding is consistent with prior studies documenting that increased (perceived) client risk reduces loan maturities (Graham et al., 2008; Chan et al., 2013). Column (3) of Table 8 reports the estimation of the impact of CFO beauty on the number of covenants. The results are consistent with our prediction that banks impose fewer covenants on borrowers with more attractive CFOs. Overall, our results suggest that, in addition to lower loan spreads, banks also offer favorable non-monetary terms to CFOs with higher facial beauty.

We also investigate the relation between CFO facial attractiveness and loan syndicate structure. We conjecture that more facially attractive CFOs are better at communicating with bankers, and thus reduce the perceived credit risk of the lending syndicate. This would in turn reduce the number of lenders in the syndicate because the demand for loan portfolio diversification by lenders (i.e., sharing of risk) will be lower. The coefficient on *CFO Beauty* in column (4) of Table 8 is negative and statistically significant, indicating that the number of lenders is smaller for firms with more attractive CFOs, which is consistent with our conjecture.

In additional tests, we examine whether lenders charge lower fees to borrowers whose CFOs have greater facial attractiveness. Prior literature suggests that fees are associated with default risk because monitoring costs increase with default risk. (e.g., Graham et al., 2008). Columns (5) and (6) of Table 8 show negative and statistically significant associations between CFO facial attractiveness and both annual fees (coefficient = –3.872, t-stat. = –2.92) and upfront fees (coefficient = –0.145, t-stat. = –3.43).[22] In column (7) of Table 8, we include loan size as an additional dependent variable. We do not find a statistically significant relation between loan size and CFO facial attractiveness.

[Insert Table 8 about here]

Overall, our results relating CFO facial attractiveness to non-price loan terms are consistent with Hypothesis 4 and Graham et al.'s (2008) findings that loans initiated after accounting restatements have statistically significantly higher loan spreads, shorter maturities, higher likelihood of being secured, and more covenant restrictions. Next, we summarize the results of several additional tests that we conduct to strengthen the validity of our findings.

5. Additional tests

5.1. Sensitivity to addition of more controls

We conduct several sensitivity tests to assess the robustness our findings. First, our results could be driven by omitted variables, such as firm's financial performance, default risk, or other CFO attributes. To test whether our results are sensitive to different measures of default probability, we include additional variables related to default risk. Specifically, we control for the probability of bankruptcy (*O-score*, based on Ohlson (1980)), credit ratings (*Investment Grade* and *Rated*), expected default frequency (*EDF*, based on Merton (1974)), and default risk (*Default Risk*, as

[22] In untabulated results, we also re-estimate the models in Table 7 using seemingly unrelated regression because the error terms could be correlated across the equations. The results are qualitatively unchanged.

defined by Bharath et al. (2008)). Because the inclusion of these variables significantly reduces our sample size, we do not include these variables in our main tables. The results presented in panel A of Table 9 show that all the risk proxies are associated with loan spread in the expected direction. The negative and significant coefficients on *CFO Beauty* indicate that our results are robust to controlling for these additional risk measures.

[Insert Table 9 about here]

Second, because our results could be driven by the two other important facial characteristics, i.e., trustworthiness (*CFO Trustworthiness*, based on Hsieh et al., 2020) and competence (*CFO Competence*, based on Peng et al., 2022), we re-estimate our models after including these variables as additional controls. Columns 1–3 in panel B of Table 9 show that although both *CFO Trustworthiness* and *CFO Competence* are negatively and statistically significantly associated with loan costs, the impact of our facial beauty measure remains negative and statistically significant over and above the two important traits (Li et al., 2023).

Third, although it is usually CFOs who negotiate with the banks or other financial institutions when seeking a loan, CEOs may also play a role when banks make loan decisions, and consequently CEO facial attractiveness may also impact bank loan costs. Therefore, we control for CEO beauty. The results in column (1) of Table 9, panel C show that the relation between CEO beauty and loan spread is negative but not statistically significant. The results in column (2), when both CEO beauty and CFO beauty are included as independent variables, show that the coefficient on CFO beauty is negative and statistically significant but the coefficient on CEO beauty is not statistically significant. These results further confirm that it is CFO facial attractiveness that influences banks' lending decisions.

5.2. Turnover analysis

Despite controlling for firm fixed effects in our main analyses, we conduct a short window change analysis around CFO turnover events, as a sensitivity analysis. We regress the change in loan spread (Δ *Loan Spread*) from each of the last two years of the outgoing CFO's tenure to the first two years of the incoming CFO's tenure on the corresponding changes in CFO beauty and changes in all continuous control variables. The results in columns (1) and (2) of Table 10 exhibit a statistically significant association between change in loan spread and change in CFO beauty. These results are consistent with our main findings and reinforce our identification of a significant negative relation between bank loan cost and CFO facial attractiveness.

[Insert Table 10 about here]

5.3. Comparison with the bond market and actual default probabilities

One alternative explanation for our results is that CFO facial attractiveness is associated with other non-observable CFO characteristics such as managerial ability and/or firm characteristics, that we do not fully control for. Although we control for firm fixed effects, there may be other time-variant correlated omitted variables that bias our analysis. To address this concern, we investigate whether CFO facial attractiveness is negatively associated with bond yields and default probabilities. If more attractive CFOs are associated with other managerial abilities and/or other firm characteristics (e.g., financial reporting quality), then bond yields should also be lower for firms led by attractive CFOs. On the other hand, if facial attractiveness enhances CFOs' ability to communicate with and convince bankers through physical interactions, CFO beauty should have a smaller or no impact on bond yields. This "placebo" test is based on the assumption that CFO facial attractiveness plays a lesser role in the bond market than in bank-loan contracting because of the nature of the interactions (i.e., banks have much closer relationships with the firm's managers than bond holders). We report the results in Table 11.

[Insert Table 11 about here]

First, we restrict the sample to firm-years with public offerings of bonds to ensure that our analysis is not biased because only a subset of the observations have new bond issues. In panel A of Table 11, we report the results for the association between CFO facial attractiveness and bond spread (column 1) and for the association between CFO facial attractiveness and bank loan spread (column 2). The coefficient on bond spread is not statistically significant (–0.000, t-stat. = –0.68), whereas the coefficient on bank loan spread remains negative and statistically significant (–12.790, t-stat. = –1.73). These results suggest that the CFO facial attractiveness premium is driven by physical interactions.

In addition, we investigate the relation between CFO beauty and subsequent default rate in panel B of Table 11. This analysis helps us to distinguish whether the beauty premium documented in the prior analysis is driven by tasted-based or statistical discrimination. If the beauty premium is driven by taste-based discrimination, CFO facial attractiveness would not be correlated with ex-post default probability. On the other hand, if the beauty premium is associated with lower default probability, then our results could be driven, at least partly, by statistical discrimination. We find that CFO beauty is not statistically significantly related to actual default rate.[23] Collectively, the results for bond spreads and default probabilities suggest that the beauty premium documented in our study is likely to be driven by taste-based discrimination as opposed to statistical discrimination.

[23] The lack of result could be driven by the small number of defaults in our sample; only 51 defaults were experienced by firms during our sample period.

6. Conclusion

Using a machine learning-based facial beauty prediction model, this study explores whether and how CFOs' facial attractiveness impacts pricing and various other features of bank loans. The empirical evidence indicates that CFOs with higher facial attractiveness obtain bank loans with lower loan spreads, lower likelihood of being secured, longer maturity, and fewer covenants. Cross-sectional analyses and analyses of bond spreads and actual default rates suggest that the beauty premium documented in the study is likely to be driven by taste-based discrimination as opposed to statistical discrimination. This evidence adds to researchers' increased recognition that qualitative and behavioral factors, in addition to quantitative measures, can influence firms' bank loan contract terms. Our study therefore offers important insights about the impact of cognitive biases in a debt contracting setting, which also have important implications for practitioners and regulators.

Although the evidence in this study points to the beauty premium in the bank loan contracting setting being driven by taste-based discrimination (i.e., by lenders' cognitive bias in dealing with individuals with facial attractiveness), our analysis does not provide conclusive evidence about whether facial beauty should be treated as a bias factor or job-relevant trait. To further distinguish between these two effects, we suggest that future research explore whether facial attractiveness is associated with actual scores on socially desirable personality traits, such as emotional stability, extraversion, and ambition (Langlois et al., 2000).

Our results, at this stage, do not imply that there is more discrimination against less attractive CFOs during the lending negotiations, nor do we suggest eliminating facial appearance from hiring practices and legislating out beauty biases. Instead, we follow the suggestion in the opening quote of the paper and highlight the significance of the beauty bias in a loan contracting setting. Our findings suggest that banks should be cognizant of this bias, spend sufficient time during face-to-face negotiations to assess the borrower's characteristics, and gather sufficient soft information before determining pricing and other features of bank loan contracts.

APPENDIX 1
Computer-based facial attractiveness measure

We first obtain the names of CFOs of publicly traded firms in the US from the ExecComp database, and then search for a clear front photograph of each CFO using Google Images.[24]

We then follow several steps to ensure high-quality results from our image search. First, for each CFO, we search Google Images for photographs using the CFO's name and company affiliation, and download the first 10 pictures in the search results. We then delete images with either width or height smaller than 64 pixels to ensure accurate and sensitive detection. From the remaining pictures, we select those that only contain a single face using a computer algorithm based on OpenCV, which is one of the most popular libraries in the field of computer vision.[25] We follow the procedure of Kazemi and Sullivan (2014) and train a face detector algorithm to recognize 68 facial points on the pictures. Following Hsieh et al. (2020), we then calculate and compare three pairs of distances between facial points for the right and left sides of a given face to determine whether the image depicts the front view. If the differences between the two distances in each of the three pairs are all less than 20%, we classify the image as suitable for CFO beauty analysis. If any of the differences are greater than 20%, our algorithm abandons the file. If we cannot find a suitable image among the 10 pictures, our algorithm returns a missing value for the person. Finally, we manually check the pictures returned from the above algorithm to ensure that each picture contains only one front view face.

[24] https://www.google.com/imghp?hl=en

[25] We use a pre-trained classifier to detect faces, provided by OpenCV. This model provides the number of faces in an image, enabling us to retain those that only contain one face. See: https://github.com/opencv/opencv/blob/master/data/haarcascades/haarcascade_frontalface_default.xml

To construct our facial beauty measure, we utilize the SCUT_SBP5050 dataset from Liang et al. (2018).[26] This dataset contains 5,500 frontal faces with diverse properties (i.e., gender, ethnicity, age) and diverse labels (e.g., facial landmarks, beauty scores on a 5-point scale, beauty score distributions), which allows us to evaluate different computational models with different facial beauty prediction paradigms. All the images are labeled with beauty scores ranging from 1 to 5 and 68 facial landmarks/components are identified for each image.[27]

Based on these labeled data, we construct our own machine learning model that predicts the facial beauty of each executive based on the images we downloaded from Google Images. Specifically, we train a CNN (convolutional neural network)[28] model called ResNeXt-50 (He et al., 2016) using the 5,500 images from the SCUT_SBP5050 dataset, with a L2 distance error (mean square error). We resize each raw RGB[29] SCUT_SBP5050 image to 350×350 pixels and feed it into the ResNeXt-50 model. The model parameters are initialized by pretrained CNN models taken from the ImageNet database and updated by mini-batch Stochastic Gradient Descent (which is the most commonly used optimization algorithm in machine learning (Goodfellow et al., 2016); the learning rate is 0.01 and the optimizer is Adam (Kingma and Ba, 2014). We set the batch size as 32, the momentum coefficient as 0.9, and the maximum number of iterations as 10,000. We train our model on the TensorFlow platform and then test it using a test sample taken from the initial CFO sample. The test mean squared error is 0.32, which is sufficiently small compared to the mean value of the beauty measure (approximately 2.83). We then analyze our downloaded CFO images

[26] https://github.com/HCIILAB/SCUT-FBP5500-Database-Release

[27] Although in theory the images are labeled ranging from 1 to 5, in our sample CFO facial attractiveness ranges from 1.38 to 4.35.

[28] A convolutional neural network is a type of deep neural network most commonly used in image processing. See: https://en.wikipedia.org/wiki/Convolutional_neural_network#cite_note-28

[29] RGB is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. See: https://en.wikipedia.org/wiki/RGB_(disambiguation)

using the trained model and obtain beauty measures for the CFOs. Some images of CFOs do not yield a measure because we must resize the downloaded images to 350×350, which causes some low-quality images to be unusable. We are able to infer attractiveness scores for 1,769 CFOs, representing 8,435 firm-year observations from 2006 to 2019.

APPENDIX 2

External validation of the facial attractiveness measure

We conduct the following experiment to verify that our measure of facial attractiveness is a legitimate proxy for real human perceptions.

We follow Hsieh et al. (2020) and randomly select a set of twenty pictures of the CFOs in our sample (four images from each quintile of our facial beauty measure), and survey 500 independent raters on Amazon Mechanical Turk (MTurk) to obtain their assessments of the facial attractiveness of these twenty CFOs. The twenty pictures of the CFOs are shown to participants in a random sequence without disclosing the identities of the CFOs. We ask the participants the following question: "How attractive is this person in the picture?" Participants are asked to rank each picture on a seven-point scale from 1 (*not attractive at all*) to 7 (*extremely attractive*). For each picture, we average responses across all participants to obtain an average facial beauty rating (*Beauty Score*). Panel A in this appendix reports the results. The mean *Beauty Score* is 5.28 for most attractive CFOs (quintile 5) and 3.58 for the least attractive CFOs (quintile 1). The difference between the two ratings is highly statistically significant ($p < 0.01$), suggesting that human ratings of facial beauty are consistent with our machine-learning based ratings.

We then conduct a follow up test to validate the conjecture that people are more willing to communicate with CFOs who have greater facial attractiveness. Following the procedures established by behavioral experimentalists such as Belk (1975) and Keller (1987), we show the twenty pictures of the CFOs to participants in another random sequence without disclosing the identities of the CFOs and ask the participants the following question for each image: "Are you willing to communicate with this person in the picture?" Similar to the first test, responses were given on a seven-point scale from 1 (*not willing at all*) to 7 (*extremely willing*) for each picture. The results are reported in panel B of this appendix. The mean willingness to communicate is 5.38

for the most attractive CFO (quintile 5) and 4.53 for the least attractive CFO (quintile 1), and the difference between the two scores is highly statistically significant ($p < 0.01$). Overall, our external validity checks confirm that our machine-learning based facial beauty measure provides a valid proxy for human perceptions of beauty and willingness to communicate.

We then calculate the Pearson correlation coefficient between the mean facial attractiveness rating from the 500 raters and our machine-generated beauty index. The correlation coefficient is 0.835 and the correlation is significant at the 1% level. The magnitude of the correlation coefficient is similar to the correlation coefficient of 0.834 documented by Hsieh et al. (2020). In addition, we conduct a multivariate analysis to examine the relation between the machine-based and human-based measures. Specifically, we treat each human evaluation as an independent observation (10,000 in total) and regress the human-based facial measures on our machine-based measures. We control for rater differences by including rater fixed effects and adjust standard errors for cross-sectional correlation by two-way clustering of CFOs and raters. The results, reported in panel C of this appendix, indicate that our machine-based measures are strongly related to the human perceptions. Collectively, the evidence from these two experiments indicates that human ratings of facial attractiveness are consistent with our computer-generated ratings.

As a sensitivity test, we also compare the facial beauty measures of male and female CFOs in our sample. On average, male CEOs in our sample have higher facial attractiveness than female CFOs (results of this comparison are provided in panel D of this appendix). When we repeat our main analysis using subsets of male and female CFOs, the results are similar to our main findings (results not tabulated).

Panel A: Facial attractiveness				95% Confidence Interval	
Quintile	N	Mean	St. Deviation	Lower Bound	Upper Bound
1	2,000	3.58	1.78	3.50	3.66
2	2,000	4.37	1.50	4.31	4.44
3	2,000	4.97	1.37	4.91	5.03
4	2,000	5.17	1.33	5.11	5.23
5	2,000	5.28	1.39	5.22	5.34
	10,000	4.68	1.61	4.64	4.71
Difference 1-5		1.10***			

Panel B: Willingness to communicate				95% Confidence Interval	
Quintile	N	Mean	St. Deviation	Lower Bound	Upper Bound
1	2,000	4.53	1.81	4.45	4.60
2	2,000	4.98	1.64	4.91	5.05
3	2,000	5.18	1.58	5.11	5.25
4	2,000	5.32	1.53	5.25	5.38
5	2,000	5.38	1.50	5.32	5.45
	10,000	5.08	1.64	5.04	5.11
Difference 1-5		0.55***			

Panel C: Regressions	(1)	(2)
Variables	*Beauty Score from MTurk*	*Willingness to communicate*
Our facial beauty measure	1.262***	0.640***
	(0.177)	(0.124)
Constant	1.350***	3.391***
	(0.400)	(0.321)
Observations	10,000	10,000
Rater Fixed Effects	YES	YES
Adjusted R^2	0.561	0.624

Panel D: Male vs. female CFOs			
Beauty	Female	Male	difference
Mean	2.77	2.84	–0.07***
Median	2.78	2.85	–0.07**
N	506	4,765	

Notes: We test the difference in means between the extreme quartile subsamples using a t-test and the difference in median test is based on a Wilcoxon signed rank test. ** and *** represent significance levels of 5% and 1%, respectively.

APPENDIX 3
Variable definitions

Variable name	Definition and construction
CFOs' facial features	
CFO Beauty	CFO facial beauty, constructed using a machine learning prediction model. Section 3, Appendix 1, and Appendix 2 provide detailed information on this variable.
CFO Trustworthiness	A composite measure of CFO facial trustworthiness, calculated as the average of the CFO's standardized value of reversed *Eyebrow*, standardized value of *Face Shape*, standardized value of *Chin Angle*, and standardized value of reversed *Philtrum*. Each standardized facial feature score is computed as the facial feature minus the sample mean, scaled by the sample standard deviation (Hsieh et al., 2020).
CFO Competence	A measure of a CFO's facial appearance of competence. We construct this measure as in Peng et al. (2022).
Loan characteristics	
Loan Spread	The amount the borrower pays in basis points over LIBOR for each dollar drawn down.
Loan Size	The amount of the loan facility in million USD.
Ln (Loan Size)	Natural logarithm of the amount of the loan facility in million USD.
Maturity	The number of months to maturity.
Ln (Maturity)	Natural logarithm of the number of months to maturity.
Secured	An indicator variable that equals 1 if the loan facility is secured by collateral, and 0 otherwise.
# Covenants	The total number of covenants in the loan contract.
# Lenders	The total number of syndicated lenders for a single loan.
Upfront Fee	The fee paid by the borrower upon closing of a loan (measured in basis points).
Annual Fee	Annual charge for the loan facility (also called facility fee), measured in basis points relative to the total loan facility amount (used or unused).
Firm-level variables	
Size	Natural logarithm of total assets in million USD.
ROA	Earnings before interest, tax, depreciation, and amortization, scaled by total assets.
Leverage	Current debt and long-term debt scaled by total assets.
Operational Risk	Standard deviation of yearly cash flows from operations divided by total assets, calculated over the past five fiscal years.
Tangibility	Gross property, plant, and equipment scaled by total assets.
Altman Z	Modified Altman (1968) Z-score, computed as Z-score = (1.2 x working capital + 1.4 x retained earnings + 3.3 x income before extraordinary items + 0.999 x sales) / total assets.
MB	Market-to-book ratio, calculated as the market value of equity divided by the book value of equity.
O-score	Ohlson's (1980) O-Score, computed as O = –1.32 – 0.407 (log total assets) + 6.03 (total liabilities / total assets) – 1.43 (working capital /

	total assets) + 0.076 (current liabilities / current assets) – 1.72 (1 if total liabilities > total assets, 0 otherwise) – 0.521 ((net income$_t$ - net income$_{t-1}$)/(| net income$_t$| + | net income$_{t-1}$|))
EDF	A measure of the expected default frequency computed based on the Merton (1974) bond pricing model.
Rated	An indicator variable that equals 1 if the firm has credit rating, and 0 if it does not have a credit rating.
Investment Grade	An indicator variable that that equals 1 if the firm's debt is rated as investment grade by SandP, and 0 otherwise.
Default Risk	Following Bharath et al. (2008), *Default Risk* equals 0.3064×*Altman Z* + 0.5141×*O-score* + 0.4317×*EDF* – 0.4258×*Rated* + + 0.5237×*Investment grade*.
Manager-level variables	
CFO Gender	An indicator variable that equals 1 if the CFO is male, and 0 otherwise.
CFO Age	Age of the CFO.
CEO Gender	An indicator variable that equals 1 if the CEO is male, and 0 otherwise.
CEO Age	Age of the CEO.
Cross-sectional analysis variables	
Large Bank	An indicator variable that equals 1 if the total amount of loans issued by the lender during the client's observation year is above the sample median, and 0 otherwise.
Bank Competition	An indicator variable that equals 1 if the average loan spread of the lender in the fiscal year is less than the sample median, and 0 otherwise. A higher value of loan spread indicates lower competition.
Prior Bank	An indicator variable that equals 1 if there is a previous relationship between the borrower and the lender (i.e., if the bank has dealt with the firm before the CFO joined the firm), and 0 otherwise.
Prior CFO	An indicator variable that equals 1 if there is a previous relationship between the CFO and the lender (i.e., if the CFO dealt with the lender in a prior role as CFO of a different firm), and 0 otherwise.
Distance	An indicator variable that equals 1 if the geographic distance between the bank's headquarters and the client's headquarters is greater than the sample median, and 0 otherwise.
Prior Loan	An indicator variable that equals 1 if the CFO has borrowed from the lender in the past (i.e., if the CFO has already borrowed from the lender in the past in their current position), and 0 otherwise.
CFO Tenure	An indicator variable that equals 1 if the CFO's tenure is greater than the sample median, and 0 otherwise.
Firm Age	An indicator variable that equals 1 if the number of years since the year the firm was established is above the sample median, and 0 otherwise.
Firm Size	An indicator variable that equals 1 if the firm size (natural logarithm of total assets in million USD) is above the sample median, and 0 otherwise.

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TABLE 1
Sample selection

	# Firms	# Firm-years
Sample with CFO's facial image available	2,705	14,472
Sample with CFO's facial beauty available	1,769	8,435
Filters	# Firms	# Facilities
Loans to public US borrowers with loan spread available	2,852	27,917
(Less) Observations with unavailable CEO/CFO facial data	(–1,293)	(–20,858)
(Less) Observations with missing data for control variables	(–200)	(–1,788)
Final sample	1,093	5,271

This table details our sample selection procedure. We note that there may be more than one loan contract for a given firm-year and only list the distribution of samples for which a CFO facial beauty score is available, and for which loan contracts and loan spread information are available. We search for pictures of all CFOs included in the ExecuComp database. After we merge the datasets and delete observations with missing data, the sample period is 2006 to 2016.

TABLE 2
Summary statistics

Variables	N.	Mean	25%	Median	75%	Std. Dev.
CFO Beauty	5,271	2.834	2.505	2.838	3.161	0.486
CEO Beauty	3,370	2.670	2.384	2.697	3.003	0.470
CFO Trustworthiness	5,271	–0.024	–0.282	–0.013	0.412	0.697
CFO Competence	5,271	0.161	0.027	0.173	0.332	0.239
Loan Spread	5,271	182.589	112.500	150.000	225.000	114.428
Secured	5,271	0.384	0.000	0.000	1.000	0.486
# of Covenants	5,271	1.626	0.000	1.000	3.000	1.869
Ln (# of Lenders)	5,271	2.209	1.791	2.197	2.708	0.675
Ln (Annual fee)	222	3.408	2.773	3.433	3.932	0.885
Ln (Upfront fee)	734	5.442	5.170	5.525	5.787	0.610
Size	5,271	8.618	7.481	8.574	9.715	1.643
ROA	5,271	0.121	0.080	0.111	0.154	0.072
Leverage	5,271	0.297	0.171	0.288	0.406	0.174
Operational Risk	5,271	0.040	0.016	0.028	0.048	0.041
Tangibility	5,271	0.482	0.147	0.350	0.770	0.402
MB	5,271	2.869	1.267	1.972	3.230	2.968
Altman Z	5,271	3.121	1.515	2.593	3.991	2.468
ln (Loan Size)	5,271	5.974	5.165	5.991	6.908	1.336
ln (Maturity)	5,271	3.854	3.807	4.111	4.111	0.569
CFO Tenure	5,271	0.416	0.000	0.000	1.000	0.493
CFO Gender	5,271	0.904	1.000	1.000	1.000	0.295
CFO Age	5,271	50.528	46.000	51.000	55.000	6.317
Prior Loan	5,271	0.271	0.000	0.000	1.000	0.444
O-score	5,271	–1.242	–1.985	–1.211	–0.534	1.114
EDF	4,231	0.073	0.000	0.000	0.131	0.121
Investment Grade	3,693	0.792	1.000	1.000	1.000	0.059
Rated	5,271	0.701	0.000	1.000	1.000	0.458
Default Risk	3,350	0.289	0.126	0.249	0.396	1.603
Large Bank	5,271	0.497	0.000	0.000	1.000	0.500
Bank Competition	5,102	0.493	0.000	0.000	1.000	0.500
Prior Bank	5,271	0.476	0.000	0.000	1.000	0.492
Prior CFO	5,271	0.049	0.000	0.000	0.000	0.215

This table shows summary statistics for CFOs' facial beauty measurements and other variables. The sample period is from 2006 to 2016. All variables are as defined in Appendix 3.

TABLE 3
Correlations

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Loan Spread (I)																				
CFO Beauty (II)	**–0.165**																			
CFO Trustworthiness (III)	–0.005	0.021																		
CFO Competence (IV)	–0.012	0.012	0.022																	
Secured (V)	**0.422**	**–0.119**	**–0.151**	**–0.112**																
# Covenants (VI)	**0.213**	**–0.067**	**–0.043**	**–0.062**	**0.526**															
# Lenders (VII)	**–0.340**	0.025	**0.203**	**0.272**	**–0.328**	–0.050														
Annual Fee (VIII)	**0.636**	–0.028	–0.032	**–0.072**	**0.558**	**0.481**	**–0.302**													
Upfront Fee (IX)	**0.870**	**–0.187**	**–0.081**	–0.012	**0.533**	**0.222**	**–0.289**	**0.569**												
Size (X)	**–0.244**	**0.082**	0.012	**0.212**	**–0.331**	**–0.285**	**0.379**	**–0.494**	**–0.216**											
ROA (XI)	**–0.182**	0.030	0.024	**0.142**	**–0.080**	–0.011	0.007	0.054	**–0.222**	**–0.246**										
Leverage (XII)	**0.255**	**–0.061**	**0.158**	**0.054**	**0.184**	**0.058**	**–0.058**	0.052	**0.311**	**0.140**	**–0.097**									
Operational Risk (XIII)	**0.147**	**–0.064**	**0.099**	**0.192**	**0.175**	**0.121**	**–0.132**	**0.259**	**0.104**	**–0.254**	**0.076**	**–0.045**								
Tangibility (XIV)	0.025	**–0.069**	0.004	**0.142**	–0.009	**–0.051**	–0.004	**–0.125**	0.005	**–0.062**	**0.134**	**0.151**	–0.008							
MB (XV)	**–0.081**	0.005	**0.103**	**–0.121**	–0.010	–0.010	**–0.055**	**0.174**	–0.038	**–0.101**	**0.400**	**0.106**	**0.114**	**–0.077**						
Altman Z (XVI)	**–0.210**	**0.058**	**–0.082**	**–0.224**	**–0.067**	0.012	**–0.085**	**0.194**	**–0.247**	**–0.363**	**0.572**	**–0.456**	**0.136**	**–0.121**	**0.353**					
Loan Size (XVII)	**–0.241**	**0.047**	0.023	**0.213**	**–0.243**	**–0.135**	**0.299**	**–0.556**	**–0.168**	**0.613**	**–0.047**	**0.101**	**–0.176**	0.002	**0.044**	**–0.149**				
Maturity (XVIII)	**0.078**	0.005	**0.122**	0.042	**0.198**	**0.089**	–0.038	0.047	**0.241**	**–0.205**	**0.057**	**0.090**	**–0.032**	**0.067**	0.025	**0.033**	**–0.061**			
CFO Gender (XIX)	**0.045**	0.040	**0.193**	–0.013	**0.047**	0.013	–0.005	**0.179**	**0.062**	–0.017	**–0.062**	**0.084**	–0.020	0.018	0.017	**–0.047**	**–0.035**	–0.007		
CFO Age (XX)	**–0.093**	0.039	**–0.082**	**0.072**	**–0.087**	**–0.084**	**–0.082**	**–0.205**	–0.011	**0.066**	0.034	–0.035	**–0.044**	0.000	**–0.028**	0.011	**0.051**	–0.022	**0.063**	

Pearson correlation values in bold denote significance at 5%.

TABLE 4
Main regression results

	Dependent variable: *Loan Spread*		
	(1)	(2)	(3)
CFO Beauty	–**38.745*****	–**19.319*****	–**14.306*****
	(–12.12)	**(–4.53)**	**(–2.79)**
Size		–18.406***	–9.050*
		(–7.72)	(–1.87)
ROA		–268.248***	–195.644***
		(–6.16)	(–5.56)
Leverage		166.660***	204.490***
		(8.86)	(10.17)
Operational Risk		186.270***	53.829
		(3.22)	(1.14)
Tangibility		–38.555***	–67.192***
		(–4.38)	(–4.65)
MB		–1.064	–0.857
		(–1.27)	(–0.97)
Altman Z		–3.509**	1.194
		(–2.56)	(0.76)
Ln (Loan Size)		–8.630***	–5.817***
		(–3.93)	(–4.47)
Ln (Maturity)		1.952	–7.528***
		(0.49)	(–3.20)
CFO Gender		12.356*	12.054
		(1.83)	(1.50)
CFO Age		–0.672*	–0.378
		(–1.85)	(–1.01)
Intercept	292.385***	400.673***	300.844***
	(31.80)	(12.37)	(5.97)
Fixed Effects	No	Industry, Year	Firm, Year
F	46.82	58.29	69.85
Adjusted R^2	0.027	0.478	0.604
N	5,271	5,271	5,271

This table shows results for the relation between CFO beauty and loan spread. The sample period is from 2006 to 2016. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. T-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 5
Cross-sectional tests of borrowing firm characteristics

	Dependent variable: *Loan Spread*			
	(1)	(2)	(3)	(4)
CFO Beauty	**–39.233*******	**–54.944*******	**–19.163*******	**–63.842*******
	(–4.35)	**(–3.72)**	**(–5.82)**	**(–4.62)**
CFO Beauty * Firm Size	**11.840****			**14.102****
	(2.13)			**(2.06)**
CFO Beauty * Firm Age		**27.031*******		**12.201****
		(2.95)		**(2.05)**
CFO Beauty * Rated			**10.967****	**11.617****
			(2.16)	**(2.53)**
Firm Size	–61.119***			–69.530***
	(–3.79)			(–3.55)
Firm Age		–88.281***		–48.350***
		(–3.31)		(–2.84)
Rated			–19.736***	–44.255**
			(–3.11)	(–2.04)
Intercept	364.086***	436.679***	440.171***	457.928***
	(11.51)	(6.70)	(19.38)	(10.58)
Controls	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
F	109.49	64.66	114.06	94.95
Adjusted R^2	0.605	0.605	0.607	0.608
N	5,271	5,271	5,271	5,271

This table shows results for the impact of firm size, firm age, and availability of credit ratings on the relation between CFO beauty and loan spread. Controls are the same as in Table 4. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. T-statistics are reported in parentheses. ** and *** represent significance levels of 5% and 1%, respectively.

TABLE 6
Cross-sectional tests of CFO characteristics

	Dependent variable: *Loan Spread*			
	(1)	(2)	(3)	(4)
CFO Beauty	**–24.963*****	**–21.604*****	**–19.401*****	**–32.277*****
	(–5.00)	**(–5.90)**	**(–3.40)**	**(–5.75)**
CFO Beauty* × *CFO Tenure	**16.655*****			**11.025 ****
	(4.00)			**(2.34)**
CFO Beauty* × *Prior Loan		**12.801****		**19.524*****
		(2.39)		**(2.90)**
CFO Beauty* × *Prior CFO			**9.471***	**15.395**
			(1.86)	**(1.58)**
CFO Tenure	–26.289***			–25.798*
	(–2.95)			(–1.86)
Prior Loan		–28.188*		–34.949*
		(–1.85)		(–1.98)
Prior CFO			–36.238**	–40.658***
			(–2.47)	(–2.67)
Intercept	377.906***	309.673***	312.095***	414.122***
	(9.20)	(6.08)	(6.15)	(9.84)
Controls	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adjusted R^2	0.606	0.605	0.607	0.607
N	5,271	5,271	5,271	5,271

This table shows results for the impact of CFO tenure, CFO's first bank loan, and bank's prior experience with the borrower on the relation between CFO beauty and loan spread. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. Controls are the same as in Table 4. T-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 7
Cross-sectional tests of lender characteristics

	Dependent variable: *Loan Spread*				
	(1)	(2)	(3)	(4)	(5)
CFO Beauty	**–28.838*****	**–22.609*****	**–18.212*****	**–13.250****	**–28.141*****
	(–4.51)	**(–6.13)**	**(–3.26)**	**(–2.11)**	**(–3.59)**
CFO Beauty × Large Bank	**23.389*****				**18.407*****
	(4.00)				**(3.32)**
CFO Beauty × Bank Competition		**10.801****			**7.366****
		(2.20)			**(2.21)**
CFO Beauty × Prior Bank			**8.274***		**2.728**
			(1.82)		**(1.56)**
CFO Beauty × Distance				**6.478***	**9.748**
				(1.96)	**(1.45)**
Large Bank	**–78.848*****				**–56.925*****
	(–4.68)				**(–3.54)**
Bank Competition		**–67.388*****			**–44.172*****
		(–4.71)			**(–2.77)**
Prior Bank			**–27.400****		**–9.966**
			(–2.09)		**(–0.71)**
Distance				**–5.087**	**–15.302**
				(–0.26)	**(–0.78)**
Intercept	366.042***	431.905***	313.678***	332.243***	388.757***
	(7.41)	(19.61)	(6.18)	(6.10)	(6.98)
Controls	YES	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adjusted R^2	0.605	0.611	0.605	0.622	0.628
N	5,271	5,271	5,271	4,609	4,609

This table shows results for the impact of lender's size, competition landscape, and prior relationship with the borrower and physical distance to the borrower on the relation between CFO beauty and loan spread. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. Controls are the same as in Table 4. T-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 8
Other loan contracting terms

	Dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Secured	*Ln (Loan Maturity)*	*# Covenants*	*Ln (# Lenders)*	*Annual Fee*	*Upfront Fee*	*Ln (Loan Size)*
CFO Beauty	**–0.052****	**0.057***	**–0.190****	**–0.006****	**–3.872*****	**–0.145*****	**–0.028**
	(–2.45)	**(1.68)**	**(–2.02)**	**(–2.17)**	**(–2.92)**	**(–3.43)**	**(–0.46)**
Size	–0.057***	–0.063**	–0.262***	0.121***	–1.192	–0.163***	0.506***
	(–2.89)	(–1.97)	(–2.94)	(3.79)	(–0.77)	(–7.10)	(8.89)
ROA	–0.192	0.754***	0.954	0.655***	16.101***	–2.621***	–0.100
	(–1.32)	(3.24)	(1.47)	(2.82)	(3.64)	(–6.49)	(–0.24)
Leverage	0.425***	–0.092	1.128***	–0.139	–0.278	0.882***	–0.121
	(5.13)	(–0.69)	(3.04)	(–1.05)	(–0.10)	(4.59)	(–0.50)
Operational Risk	0.239	–0.131	–0.371	0.019	21.696	1.141**	–0.483
	(1.23)	(–0.42)	(–0.43)	(0.06)	(0.80)	(2.37)	(–0.86)
Tangibility	–0.097	0.162*	–0.340	–0.128	–1.699	0.029	–0.077
	(–1.63)	(1.70)	(–1.28)	(–1.35)	(–0.46)	(0.30)	(–0.45)
MB	0.002	0.007	–0.011	–0.004	0.402***	–0.000	0.012
	(0.65)	(1.25)	(–0.65)	(–0.75)	(2.80)	(–0.04)	(1.18)
Altman Z	–0.010	–0.021**	–0.023	–0.025**	–0.338	–0.015	–0.010
	(–1.47)	(–2.04)	(–0.78)	(–2.43)	(–0.85)	(–0.88)	(–0.54)
Ln (Loan Size)	–0.008	0.026***	0.130***	0.103***	0.019	–0.034*	
	(–1.44)	(3.01)	(5.43)	(12.03)	(1.29)	(–1.94)	
Ln (Maturity)	0.058***		–0.064	0.255***	0.115**	0.208***	0.085
	(6.03)		(–1.47)	(16.41)	(2.09)	(5.63)	(0.89)
CFO Gender	0.011	–0.045	–0.198	0.018	0.000	–0.133	0.000
	(0.34)	(–0.85)	(–1.34)	(0.34)	(0.00)	(–1.28)	(0.06)
CFO Age	0.001	–0.006***	0.005	–0.000	0.397*	–0.008***	1.315**
	(0.69)	(–2.58)	(0.75)	(–0.03)	(1.69)	(–2.60)	(2.19)
Intercept	0.802***	4.376***	4.144***	–0.281	1.707	6.268***	1.315**
	(3.86)	(13.40)	(4.46)	(–0.84)	(0.20)	(16.35)	(2.19)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
F	7.56	12.39	15.92	26.83	20.97	24.14	18.14
Adjusted R^2	0.629	0.326	0.496	0.505	0.982	0.660	0.589
N	5,271	5,271	5,271	5,271	222	734	5,271

This table shows results for the impact of CFO beauty on other loan contracting terms. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. T-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 9
Robustness tests

Panel A: Controlling for additional default probability measures

	Dependent variable: *Loan Spread*				
	(1)	(2)	(3)	(4)	(5)
CFO Beauty	**–15.201*** **	**–19.208*** **	**–14.814*** **	**–14.289*** **	**–20.508*** **
	(–2.82)	**(–3.46)**	**(–2.90)**	**(–2.79)**	**(–3.51)**
O-score	7.621**				
	(2.22)				
Investment Grade		–84.809***			
		(–3.77)			
Rated			–29.119***		
			(–4.58)		
EDF				11.122***	
				(3.21)	
Default Risk					25.570***
					(2.77)
Intercept	290.797***	421.453***	365.408***	300.762***	335.774***
	(5.39)	(5.69)	(7.00)	(5.97)	(4.33)
Controls	YES	YES	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
F	61.73	47.54	68.04	66.80	42.85
Adjusted R^2	0.589	0.647	0.606	0.604	0.633
N	4,839	3,693	5,271	4,231	3,350

Panel B: Controlling for other facial characteristics

	Dependent variable: *Loan Spread*		
	(1)	(2)	(3)
CFO Beauty	**–20.610*** **	**–19.281*** **	**–20.565*** **
	(–4.98)	**(–4.52)**	**(–4.98)**
CFO Trustworthiness	**–11.731*** **		**–11.658*** **
	(–3.22)		**(–3.21)**
CFO Competence		**–11.189** **	**–10.867** **
		(–2.31)	**(–2.24)**
Intercept	402.801***	402.896***	404.947***
	(12.47)	(12.46)	(12.55)
Controls	YES	YES	YES
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Adjusted R^2	0.680	0.678	0.680
N	5,271	5,271	5,271

TABLE 9 – continued

Panel C: Controlling for CEO facial beauty

	Dependent variable: *Loan Spread*	
	(1)	(2)
CFO Beauty		**–13.082*****
		(–2.60)
CEO Beauty	**–8.510**	**–7.941**
	(–1.56)	**(–1.45)**
CEO Gender	12.093	11.222
	(0.80)	(0.78)
CEO Age	–0.992	–0.979***
	(–0.65)	(–2.65)
CFO Gender		22.972***
		(2.96)
CFO Age		0.064
		(0.15)
Intercept	370.569***	402.453***
	(8.20)	(8.84)
Controls	YES	YES
Fixed Effects	Firm, Year	Firm, Year
Adjusted R^2	0.507	0.511
N	3,370	3,370

Panel A reports results after controlling for alternative default risk measures; Panel B reports results after controlling for alternative CFO facial characteristics; and Panel C reports results after controlling for CEO facial characteristics. Controls are the same as in Table 4. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. All variables are defined in Appendix 3. T-statistics are reported in parentheses. ** and *** represent significance levels of 5% and 1%, respectively.

TABLE 10
CFO turnover analysis

	Dependent variable: Δ *Loan Spread*	
	(1)	(2)
	(t-1 to t+1)	(t-2 to t+2)
Δ ***CFO Beauty***	**–40.585****	**–25.370****
	(–2.46)	**(–2.15)**
Δ *Size*	8.456	13.797
	(0.39)	(0.87)
Δ *ROA*	17.000	–110.306
	(0.11)	(–0.94)
Δ *Leverage*	169.634*	154.576**
	(1.88)	(2.13)
Δ *Operational Risk*	80.110	–193.597
	(0.31)	(–1.07)
Δ *Tangibility*	–163.525**	–132.790***
	(–2.31)	(–2.84)
Δ *MB*	1.183	2.013
	(0.32)	(0.76)
Δ *Altman Z*	5.704	2.514
	(0.77)	(0.40)
Δ *Ln (Loan Size)*	–2.152	–5.169
	(–0.31)	(–0.99)
Δ *Ln (Maturity)*	12.001	–10.150
	(0.92)	(–0.90)
Δ *CFO Gender*	40.064**	25.967
	(2.13)	(1.40)
Δ *CFO Age*	–0.405	–0.366
	(–0.48)	(–0.45)
Intercept	199.772**	135.197***
	(2.37)	(3.13)
Fixed Effects	Firm, Year	Firm, Year
F	3.02	3.57
Adjusted R^2	0.397	0.439
N	334	206

This table shows results for the impact of CFO beauty on loan spread when there are turnovers. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. T-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 11
Channel analysis

Panel A: CFO beauty and bond yields

	(1) *Bond Spread*	(2) *Loan Spread*
CFO Beauty	**–0.000**	**–12.790***
	(–0.68)	**(–1.73)**
Intercept	0.009*	237.899**
	(1.91)	(2.32)
Controls	YES	YES
Fixed Effects	Firm, Year	Firm, Year
F	27.62	19.28
Adjusted R^2	0.606	0.653
N	1,244	1,244

Panel B: CFO beauty and probability of future default

	Dependent variable: *Default*	
	Default within 3 years	Default within 5 years
CFO Beauty	**–0.002**	**–0.006**
	(–0.35)	**(–0.85)**
Intercept	0.052	–0.050
	(1.12)	(–0.79)
Controls	YES	YES
Fixed Effects	Firm, Year	Firm, Year
F	3.05	0.87
Adjusted R^2	0.069	0.331
N	5,271	5,271

Panel A reports results for the relation between CFO beauty and bond spread (based on the aggregated loan level) and the result for CFO beauty and loan spread in the bond sample. Panel B reports results for the relation between CFO beauty and future default and the result for CFO beauty and loan spread. Controls are the same as in Table 4. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. T-statistics are reported in parentheses. * and ** represent significance levels of 10% and 5%, respectively.