

**Beyond Monetary Incentives: The Role of Meaning in
Professional Behavior and Performance**

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Abstract

We study whether demand for meaning shapes human capital allocation and information production in capital markets. Whether such nonpecuniary motives affect labor-market reallocation and the production of value-relevant information remains an important open question. Using milestone ages (ages ending in 9) as a predictable shock to heightened introspection, we first show that individuals are more likely to quit their jobs, switch employers, and relocate internationally, without moving to higher-paying or more senior positions. We then examine financial analysts, capital-market intermediaries whose professional judgment directly affects firms' information environments and market efficiency. Milestone-age analysts issue bolder, more accurate, and more timely forecasts that elicit larger market reactions, consistent with reduced career concerns and less herding. Our tests exploit within-person variation and, for analysts, compare forecasts for the same firm in the same year. These results indicate that demand for meaning affects not only whether human capital is reallocated across jobs, but also analyst performance, firms' information environments, and the dissemination of value-relevant information. Survey evidence supports value alignment and purpose-seeking as underlying mechanisms. Overall, our findings highlight nonpecuniary motives as an important behavioral force shaping agency frictions, financial human capital, and capital-market outcomes.

Keywords: Financial analysts; Information production; Demand for meaning; Behavioral finance

JEL Classifications: G14, G24, G41, J24, J63

1 Introduction

Traditional contracting models emphasize the role of pecuniary incentives in attracting talent, aligning interests, and boosting productivity (e.g., [Jensen and Meckling 1976](#); [Prendergast 1999](#); [Kaplan and Rauh 2010](#)). Yet these tools have their limitations, particularly as artificial intelligence increasingly automates routine tasks and raises the relative importance of discretionary effort, independent judgment, and creativity. The meaning individuals attach to their work may become more important in motivating behaviors that formal incentives cannot fully contract on. In particular, monetary incentives are insufficient to mitigate agency frictions, such as informational herding and career concerns, and also fail to facilitate efficient human capital allocation ([Bertrand and Mullainathan, 2003](#); [Hong and Kubik, 2003](#); [Harford et al., 2019](#); [Ladika and Sautner, 2020](#)). These frictions are particularly consequential in financial markets, where they can distort information production, impair price discovery, and ultimately affect firm value ([Clement and Tse, 2005](#); [Jackson, 2005](#)).

While monetary incentives and monitoring remain critical, individuals also value meaning at work, broadly defined as a sense of purpose, impact, and alignment with one's values ([Frankl, 1985](#); [Rosso et al., 2010](#)). Over 90% of U.S. employees are willing to trade a percentage of their lifetime earnings for greater meaning at work ([Achor et al., 2018](#)). Generations Z, Millennials, and Boomers each rank purpose ahead of paycheck as a factor driving them to work hard.¹ Existing studies on meaning largely examine *private* behavior or workplace outcomes outside financial market settings (e.g., [Steger et al. 2011](#); [Ashraf et al. 2025](#)). Evidence on whether and how demand for meaning shapes capital market-relevant professional behavior remains limited in finance.

¹<https://www.monster.com/career-advice/article/gen-z-boss-0816>.

In this paper, we examine whether a heightened demand for meaning influences individuals' professional choices and behavior in capital markets. This question is important because the efficient allocation of human capital and the independence of financial intermediaries are critical to corporate operations and overall capital market efficiency. Demand for meaning may prompt individuals to exit poorly matched positions and influence the effort and risk-taking within a given professional role. In doing so, such non-pecuniary motives may alleviate agency frictions that are not fully resolved by monetary incentives, with implications for information production and price discovery.

Although a desire for meaning may shape professional behaviors, its impact is uncertain. Work can provide a key source of meaning through personal growth, goal achievement, and social connections (Steger et al., 2009). However, career concerns and standard contracting frictions may constrain individuals' ability to act on such motives. High labor market frictions and the risks associated with career transitions may discourage professionals from pursuing meaningful changes at work. Instead these individuals may focus purely on private behaviors (Alter and Hershfield, 2014). Thus, whether pursuit of meaning affects human capital and capital-market behavior remains an open empirical question.

Testing our research question requires an empirical proxy of 'demand for meaning' that is both individual-specific and time-varying. Because meaningfulness is difficult to observe directly in archival data, we follow Alter and Hershfield (2014) and use milestone ages—ages ending in 9—as a proxy for psychologically salient periods of heightened introspection and life evaluation. Prior research finds that individuals approaching a new decade in age exhibit changes in *private* behavior consistent with a search for meaning (Alter and Hershfield, 2014). Life course theory, temporal landmark theory, and relational dynamics each provide explanations of why individuals

approaching a new decade in age may experience heightened self-reflection and reassess their trajectories (see Section 2). We extend this behavioral logic to financial markets and examine whether predictable life-cycle shocks affect labor-market reallocation and information production by capital-market intermediaries.

We begin by analyzing the professional transitions of over 600,000 LinkedIn users between 1951 and 2023. Understanding the drivers of labor supply and mobility is critical, as human capital reallocation is a fundamental component of economic efficiency. Labor mobility provides a broad setting to examine whether milestone-age introspection affects the allocation of human capital. We hypothesize that the heightened introspection at milestone ages leads employees to reassess their career trajectories in search of greater alignment with their values. We expect this search for meaning to manifest in transitions such as leaving an unfulfilling role, shifting careers, relocating geographically, or moving into jobs perceived to have a stronger social mission. To test this, we construct a panel dataset detailing each individual's end-of-year employment status. We infer birth years by identifying users who list a high school with exactly three or four years of attendance and assume they turned 18 when they graduated.

Consistent with our hypothesis, we document an increase in the propensity of individuals to quit their jobs, start new jobs, and relocate internationally during the years they attain an age ending in 9. These transitions often involve career risk and non-financial tradeoffs, and are thus plausibly linked to a search for more autonomy, a reassertion of personal agency, or the pursuit of more socially meaningful work. We include individual fixed effects (absorbing all stable individual traits), country-job-year fixed effects (controlling for time-specific labor market shocks), and cohort fixed effects (accounting for generational trends). Additionally, we control for age, seniority, and tenure to ensure the observed effects are not due to career progression or general aging patterns.

The evidence suggests that during milestone ages, individuals exhibit discontinuous changes in career choices that deviate from their baseline behavior and are not explained by aging trajectories, labor market shocks, or cohort-wide effects.

An alternative explanation is that these transitions are financially motivated, reflecting a search for higher compensation or career advancement. Although increased pay or promotion and search for meaning are not incompatible, we conduct three sets of analyses to examine this alternative. First, we find that during milestone ages individuals are more likely to take a new job with a *lower* seniority level or salary. Importantly, we find no evidence that individuals are more likely to take a new job with a higher salary or seniority level during milestone ages, which is inconsistent with a purely financial motive. Second, we find that individuals are marginally more likely to switch to a prosocial occupation during milestone ages. Third, we conduct cross-sectional tests using periods of elevated macro uncertainty, which prior research suggests causes people to feel less autonomy (Matsumura and Shin, 2006; Bonaime et al., 2018). We find that the propensity to quit a job during periods of uncertainty is higher for individuals with milestone ages, consistent with heightened demand for meaning leading these individuals to seek greater alignment with intrinsic values. Collectively, these results indicate that the observed mobility patterns are less consistent with financial incentives and instead support a non-pecuniary explanation.

The LinkedIn sample provides a powerful setting to examine how demand for meaning shapes human capital reallocation using a large and diverse sample of individuals. An important follow-up question is whether the demand for meaning also influences performance when individuals remain in their existing roles. This question is particularly important in capital markets, where outcomes depend not only on the allocation of human capital across roles but also on the quality of information produced by professionals once they occupy those roles.

Evaluating such within-job changes requires a setting in which individual output is observable and comparable within a common information environment. We therefore turn to a specific financial profession: sell-side analysts. Analyst forecasts are directly relevant to capital market efficiency, and their professional environment features well-established agency frictions, including career concerns and informational herding (Jackson, 2005; Fang and Yasuda, 2009). These two settings serve complementary roles. The LinkedIn setting captures broad labor-market reallocation when individuals reassess career fit; the analyst setting narrows the analysis to a specific finance profession in which within-role behavior and market consequences are directly observable. Together, they provide a more comprehensive picture of how the demand for meaning shapes both human capital allocation and professional performance, ultimately affecting capital market outcomes.

We examine the forecasting behavior of financial analysts in China. Analysts are key capital-market intermediaries who synthesize firm information and produce forecasts used by investors, yet relatively little is known about their non-pecuniary motivations (Kothari et al., 2016). This setting has several compelling features to complement the first setting. First, we observe granular, individual-level data on analysts' information production, including forecast timeliness, boldness, accuracy, horizon, and market reactions. Second, because analysts covering the same firm vary in age, we can include firm-year fixed effects to compare analysts with and without milestone ages facing the same information environment. Third, the panel structure allows for analyst and cohort fixed effects to absorb stable individual traits and generational trends. Finally, analysts in China are required to register with the Securities Association of China (SAC), which provides verified birth years and reduces concerns about measurement in age (Alter and Hershfield, 2014).

Analysts face career concerns that create disincentives to produce bold and independent research. Previous research shows that analysts manage career risk by herding and withholding effort

(Hong et al., 2000; Clement and Tse, 2005; Brown et al., 2015). We hypothesize that milestone ages heighten analysts' motivation to demonstrate competence, a desire to meet high standards, produce informative research, and make valuable contributions to investors rather than play it safe. We expect this motivation to manifest in three ways. First, competence-seeking analysts may become more responsive and engaged, prompting them to issue forecasts more quickly following earnings announcements. Second, they may depart from consensus-driven behavior and instead issue bolder forecasts, reflecting stronger willingness to take risks. Third, their forecasts may become more accurate and informative, reflecting deeper information processing and a stronger commitment to producing value-relevant research. Together, greater forecast boldness, timeliness, and informativeness provide observable signals of competence-driven behavior plausibly tied to increased demand for meaningfulness during milestone ages.

Using over 52,000 firm-year-analyst observations from 2005 to 2021, we find evidence consistent with our hypothesis. During milestone ages, analysts are 7% more likely to issue a forecast within three days of an earnings announcement and 4.6% more likely to issue bold forecasts. Forecasts are also 5.2% more accurate and associated with 17.4% higher absolute abnormal returns, suggesting greater informativeness. We find weaker results for the All-Star analysts who already possess greater autonomy, competence, and influence in their work. Overall, these findings suggest that milestone ages trigger meaningful shifts in analysts' information production. Thus, while the LinkedIn evidence captures meaning-seeking through career reallocation, the analyst evidence shows how the demand for meaning affects behavior and performance among individuals who remain in their existing professional roles.

The observed changes in professional choices and performance during milestone ages raise the question of their underlying motives. We argue that these changes reflect heightened demand

for meaning, defined as acting in ways that align with one's values, demonstrate competence, and contribute to a broader purpose or impact. While we cannot observe this latent construct directly in our archival data, the behaviors we study, job turnover and forecast characteristics, plausibly serve as vehicles for creating meaning. To support this interpretation, we survey 514 workers on Prolific. Respondents with milestone ages are significantly more likely to report planning, seriously considering, or having recently made a professional change. When asked their motivations, those with a milestone age prioritize "better alignment between work and strengths" and "seeking more meaning and purpose in work" as their second and third most important reasons, ahead of reactive reasons (e.g., job insecurity or family change) and most strategic ones (e.g., recognition or status). These out-of-sample survey findings reinforce our interpretation that demand for meaning is an important determinant of the observed changes in behavior during milestone ages.

Although our interpretation emphasizes demand for meaning, alternative mechanisms, such as heightened anxiety or identity salience, may also be activated at milestone ages. Importantly, these channels are not inconsistent with our framework, as they may similarly reflect reassessment of misaligned roles. The nature, timing, and consistency of our documented transitions are difficult to reconcile with purely financial or mechanical explanations. Therefore, our results provide archival evidence that search for meaning can operate as an important non-pecuniary force shaping human capital, information production, and price discovery.

First, we contribute to the literature on capital-market information production by examining how nonpecuniary motives shape the behavior of information intermediaries. Existing research emphasizes how monetary incentives, career concerns, ability, and institutional conflicts shape analysts' forecast behavior and information quality (e.g., [Clement 1999](#); [Hong et al. 2000](#); [Clement and Tse 2005](#); [Jackson 2005](#); [Kadan et al. 2009](#)). We show that demand for meaning, a nonpecuniary

motive, affects the quality, independence, and market impact of information produced by capital-market intermediaries. Our evidence suggests that demand for meaning improves information production by mitigating agency frictions among these intermediaries. Our findings point to a novel behavioral source of variation in analyst information production and firms' information environments.

Second, we add to research on agency frictions, incomplete contracting, and human capital. Traditional models emphasize monetary incentives and monitoring to align interests ([Holmstrom and Milgrom, 1991](#); [Prendergast, 1999](#)). Yet professional output in financial markets depends on effort, judgment, and independence that are difficult to contract on ([Baker, 1992](#)). We provide evidence that individuals' demand for meaning can complement formal incentives and affect both the allocation and productivity of human capital. More broadly, our findings suggest that nonpecuniary motives can shape economically consequential behavior in financial markets.

Third, we contribute to behavioral finance research on life-cycle shocks and temporal landmarks. Prior research shows that temporal boundaries can alter individual motivation and behavior ([Shum, 1998](#); [Dai et al., 2014, 2015](#)). Recent finance research further suggests that milestone ages can affect retail investor risk-taking ([Cong et al., 2025](#)). We complement this literature by showing that milestone-age introspection can lead to economically consequential changes in professional behavior, including career reallocation, greater professional engagement, and more independent information production. Our evidence highlights a distinct behavioral channel through which temporal landmarks can increase the salience of nonpecuniary motives, with implications for both human capital allocation and information production by capital-market intermediaries.

2 Hypothesis Development & Empirical Framework

2.1 Hypothesis Development

Our main hypothesis is that an increased desire for meaning affects professional behaviors in capital markets. Several compelling arguments support this hypothesis. First, work plays a significant role in an individual's search for meaning (Steger and Dik, 2009). Work provides a host of experiences that foster a sense of meaning beyond being a source of financial income, with opportunities for personal growth, goal achievement, and social connections (Arvey et al., 2004; Cassar and Meier, 2018; Hussam et al., 2022). Second, individuals spend most of their time working, with over two-thirds of employees citing work as a primary source of purpose (Kirschner et al., 2022). Since finding meaningful work can be a primary contributor to having a meaningful life, we expect any amplified desire to find deeper meaning leads to changes in professional behaviors.

However, several factors may limit changes. First, monetary incentives, corporate monitoring, and the costs and uncertainty associated with changing professional behaviors (e.g., financial risks of quitting) may discourage changes in professional behaviors. Second, some professionals may already feel fulfilled and see no reason to alter their behaviors. Third, others may seek meaning outside of work, focusing on personal reassessment rather than professional changes (Kramer, 2025). Finally, efforts to create meaning likely vary widely, ranging from career advancements to maladaptive coping (Heisel and Flett, 2004), thereby complicating population-level effects. Ultimately, whether and how demand for meaning influences professional decisions remains an open empirical question.

A core empirical challenge is measuring individuals' demand for meaningfulness, which is subjective and difficult to directly observe. Prior research using surveys and experimental methods

shows that people are more likely to audit the meaningfulness of their lives as they approach a new decade in age (e.g., ages 29, 39, 49; [Alter and Hershfield 2014](#)).² Building on this literature, we treat milestone ages as psychologically salient periods that naturally trigger introspection and reassessment, and use these ages as an empirical proxy for heightened demand for meaningfulness.

The idea that specific life stages prompt reflection and behavioral adjustments is well established in psychology and sociology. Life course theory ([Elder Jr, 1998](#)) suggests that major life transitions, such as milestone ages, prompt individuals to reevaluate their life trajectories, leading to reflection, goal realignment, and proactive changes ([Costin and Vignoles, 2020](#)). Temporal landmark theory ([Shum, 1998](#)) builds on this idea, proposing that certain moments, such as birthdays or milestone ages, serve as psychological reference points that divide life into “before” and “after.” These markers encourage individuals to reconsider their choices and make forward-looking adjustments ([Dai et al., 2014, 2015](#)).

Apart from their psychological significance, milestone ages also carry societal and cultural weight and serve as socially constructed markers that shape expectations and decision-making. For instance, there are implicit societal expectations regarding when certain milestones should be achieved (e.g., completing education by 25, starting a family or buying a house by 30, and retiring by 65). These norms drive individuals to assess life progress, heightening the search for meaning. These societal expectations are further reinforced by relational dynamics—including peer influence, or workplace culture—that nudge individuals toward reassessment during milestone ages ([Elder, 1994](#)). Based on these psychological and societal mechanisms, we follow [Alter and Hershfield \(2014\)](#) to use ages ending in 9 as a proxy for individuals’ increased demand for meaning.

²While [Kühne et al. \(2015\)](#) find no evidence of milestone effects in private behaviors using German survey data, their approach has been critiqued by [Alter and Hershfield \(2015\)](#); see also [Kim et al. \(2019\)](#).

Although milestone ages provide a useful proxy for heightened demand for meaning, they may also capture other responses to temporal landmarks, including heightened anxiety, identity salience, or shifting social norms. We therefore interpret milestone ages as increasing the salience of meaning while acknowledging that adjacent mechanisms may also be activated. Our empirical tests are designed to assess whether the observed professional changes are more consistent with a meaning-based interpretation than with purely financial or mechanical ones.

2.2 Empirical Framework

We examine changes in professional behaviors during milestone ages using the following baseline ordinary least squares specification:

$$\begin{aligned} \text{Professional Behavior}_{i,t} = & \beta_0 + \beta_1 \text{Milestone age}_{i,t} + \sum \beta_{k1} \text{Controls}_{i,t} \\ & + \sum \beta_{k2} \text{Individual}_i + \sum \beta_{k3} \text{Year}_t + \sum \beta_{k4} \text{Cohort}_{i,t} + \epsilon_{i,t}. \end{aligned} \quad (1)$$

*Professional Behavior*_{*i,t*} represents one of our measures of professional behavior for individual *i* in year *t*. The independent variable of interest, *Milestone age*_{*i,t*}, is a dummy variable equal to one if individual *i* enters an age ending with 9 in year *t*, and equal to zero otherwise. *Individual*_{*i*} are fixed effects for each individual and remove all time-invariant individual characteristics (e.g., education, ethnicity, gender, and experiences before entering the profession). *Year*_{*t*} are fixed effects for each calendar year, removing any common political, economic, cultural, and societal characteristics within a given year. *Cohort*_{*i,t*} are age-cohort fixed effects (e.g., a fixed effect for ages 25–34) that account for factors constant within each age decade. We also include time-varying controls specific to each setting (e.g., age, tenure, etc.).

The coefficient β_1 captures the average change in professional behaviors during milestone ages relative to each individual's baseline performance during other ages. If milestone ages prompt individuals to pursue heightened meaning by changing their professional behaviors, we expect β_1 to differ significantly from zero. Standard errors are clustered by individual to address within-person correlation over time. For all specifications with a binary outcome, we use linear probability models due to our large number of fixed effects, as recommended by [Angrist and Pischke \(2008\)](#).

3 LinkedIn Users

3.1 Overview and Sample

In this section we examine whether individuals are more likely to change their jobs during milestone ages using a sample of over 600,000 LinkedIn users. Voluntary job changes reflect a willingness to seek opportunities that realign personal and professional values to create meaning and can have potentially profound effects on the companies that employ these individuals.

This setting has both strengths and weaknesses. On the positive side, we can track the employment decisions of a large and diverse group of individuals over multiple years, allowing us to effectively compare an individual's employment decisions during milestone and non-milestone ages. The setting thus provides both statistical power for detecting even small changes in professional behaviors and reasonable generalizability. Moreover, because LinkedIn users span a wide array of industries and job types, our findings have the potential to generalize across labor markets, offering insights into the broader implications of meaningfulness-driven career moves.

However, the data come with important limitations. First, LinkedIn profiles include both voluntary and involuntary job changes and lack details on job performance and within-job professional behaviors. To address these concerns, in the subsequent section we examine the financial analyst setting that allows us to more directly evaluate changes in job performance during milestone ages and the market consequences of any changes in professional behaviors.

Second, because LinkedIn does not report birth dates, we infer ages by identifying users who list a high school they attended for three or four years and the corresponding dates of attendance, and assuming these individuals turn 18 years old during the year they graduate. There are potential selection effects in our sample, as individuals self-select into the platform and choose what information to include in their profiles, and we focus on the subset who voluntarily provide high school information. Our sample may therefore systematically under- or over-represent certain types of workers, industries, or career trajectories and is likely skewed toward more complete or conscientious profile users. To enhance the credibility and robustness of our findings, we incorporate complementary analyses in the alternative setting that offers more direct measures of age, performance, and capital market consequences.

Table 1 Panel A outlines our LinkedIn sample from *Revelio*. We restrict it to individuals with high school information, and create a user-year panel of over 8.7 million observations with end-of-year employment information (company, location, title, seniority, and job category). We merge graduation year and drop pre-graduation employment, observations with employment gaps (four or more years), ages of 20 or less (excluding age 19 as a milestone age), and ages with fewer than 30 observations.³ To be consistent with our later sample, we drop all ages over 84. For job/country/role

³Employment changes frequently occur at the age of 19 but for reasons fundamentally different than seeking meaning.

termination analyses, we drop terminal observations as we are unable to assess whether they quit a job in that year. Our final sample includes 6,719,242 (6,003,294) user-year observations for the new job (job quit) analyses, covering 615,558 individuals across 701,246 companies in 195 countries and 150 role categories.

— Table 1 around here —

3.2 Research Design and Summary Statistics

To test our hypothesis that individuals are more likely to change their jobs during milestone ages, we examine a variety of outcome variables. First, we examine whether job changes are more common during milestone ages. Second, we examine the incentives of job changes by focusing on changes in job seniority, salary, and social impact.

To measure job changes, we create a dummy variable, *New job*_{*i,t*}, which equals 1 if individual *i* works in a company during year *t* that differs from the company they worked for at the end of year *t* – 1. Because finding a new job may take time, we also define a second dummy variable to capture employment terminations. Specifically, *Job quit*_{*i,t*} is set equal to 1 if year *t* is the last year individual *i* is employed by their current employer. We analogously code up the dummy variables *Switch country*_{*i,t*} and *Switch role*_{*i,t*}, which are set equal to one if year *t* will be individual *i*'s final year in their current country or role. To capture job changes less likely motivated by financial concerns, we define *Lower seniority*_{*i,t*} and *Lower salary*_{*i,t*} as dummy variables equal to 1 if individual *i* quits in year *t* for a new job that has a lower seniority or salary, respectively. We also capture job changes where the new position has a high prosocial score (see [Burbano](#)

et al. 2024) using the dummy variable *Prosocial job_{i,t}*. The independent variable of interest, *Milestone age_{i,t}*, equals one if individual *i* enters an age ending with 9 in year *t*.

We include individual fixed effects to capture within-individual employment changes and country-year-role fixed effects to control for role-specific factors invariant within a country-year (e.g., industry competition, job demand and supply, and nature of the role) and common time-period shocks. We also include age-cohort fixed effects to mitigate confounding from age-group characteristics. We control for the individual's logged age, job seniority (a *Revelio*-provided variable that ranges from 1 to 4 and captures the overall job position seniority) as of year $t - 1$, and the natural log of one plus the tenure for their employment position as of year $t - 1$. Our identification thus leverages within-individual deviations in employment decisions that occur specifically during milestone ages and are not explained by aging trajectories, labor market shocks, or cohort-wide effects.

Table 1 Panel B provides summary statistics for the LinkedIn sample. The unconditional probability an individual starts a new job during a given year is 24.4%. Similarly, job quits occur in 24.6% of years. Changing countries is fairly rare, with a frequency of only 2.0%, whereas changing roles is more common with a frequency of 19.8%. The unconditional probabilities that an individual leaves a company and takes a new job with a lower seniority or salary are 5.3% and 8.0%, respectively. The unconditional probability that an individual leaves a company and switches from a non-prosocial to a prosocial job is 2.3%. The average age and job-specific tenure of our users are 31.6 and 2.5 years, respectively. Figure A.1 Panel A plots the distribution of LinkedIn users' ages, which exhibits a significant right skewness (e.g., median age is 29 and minimum age is 20). Only 7.6% of LinkedIn observations align with a milestone age.

3.3 Results

Table 2 presents results for the LinkedIn sample. Columns 1 to 4 report the results of job changes. In Column 1 we analyze *New Job* and find a statistically significant 0.5% increase in the probability an individual starts a new job during a milestone age.⁴ In Column 2 we find a similarly significant increase (0.7%) in the likelihood of quitting a job during milestone ages and in Column 3 we find a 2% increase in the propensity to leave a country during milestone ages (an extreme way to try and create meaning). The results in Column 4 suggest that individuals are no more or less likely to end their current job role during milestone ages, suggesting the limits to which individuals are willing or able to seek meaning during milestone ages. Examining the control variables, we find that both age and seniority are negatively correlated with our measures of employment changes, whereas tenure is positively correlated with employment changes.

— Table 2 around here —

To examine whether such changes in employment are likely to be financially motivated, we examine changes in seniority and salary.⁵ In Table 2 Columns 5 and 6 we find that individuals are more likely to leave a company and take a new job with a lower seniority and salary during milestone ages, respectively. In untabulated results, we find no evidence that individuals are more likely to change jobs for a *higher* seniority and salary during milestone ages (p -values of 0.929 and

⁴Coefficient estimate of 0.0013 divided by the unconditional population average of 0.244.

⁵Revelio predicts the seniority using an individual's job title, company, industry, age, previous seniority, and position history. Revelio predicts the salary for each position based on role, seniority, company, and country using a regression-based model. Revelio trains this model using over 200 million salaries from job postings and publicly available labor certification applications and uses country-level inflation rates to estimate changes in salary over time. Given the way Revelio estimates seniority and salary, we exclude the control variable $Seniority_{t-1}$ in Columns 5 and 6. The sample sizes are smaller in Columns 6 through 7 due to missing salaries or prosocial ratings.

0.217, respectively). These results suggest that milestone-age transitions are not simply driven by higher pay or opportunities for career advancement, consistent with prior evidence that workers are willing to accept lower wages for greater value alignment (Leete, 2001; Chandler and Kapelner, 2013).⁶ Lastly, we examine and find in Column 7 that individuals are marginally more likely to leave a company and switch to a job with a high prosocial rating. As robustness tests, we adopt an alternative fixed effect structure (tabulated in the appendix Table A.2) and find consistent results.

Uncertainty and adversity challenge assumptions people hold about themselves and the world (e.g., predictability, security, and invulnerability), triggering existential questions and prompting individuals to seek meaning (Frankl, 1985; Updegraff et al., 2008). In Table A.3 we test the hypothesis that macroeconomic uncertainty magnifies a search for meaning, and find that individuals are more likely to quit their jobs during milestone ages if there is significant macroeconomic uncertainty (high volatility of daily returns, high GDP forecast dispersion, high levels of volatility index, and during COVID-19). Results are robust if we restrict the sample to individuals with ages ending in 7, 8, 9, 0, or 1, addressing the concern that individuals with certain ages may simply be more subject to forced turnover during periods of economic uncertainty (see Table A.4). Under low uncertainty, we find no significant evidence that milestone ages are associated with increased job quitting compared to non-milestone ages overall. However, when comparing milestone ages to immediately adjacent ages under low uncertainty, we still detect an increase in job quitting, suggesting that the milestone effect is robust and more pronounced in uncertain times.

Overall, the results suggest that individuals change their employment situation during milestone ages, ostensibly in response to an increased desire for meaning. Increased employee turnover

⁶It is challenging to completely rule out other reasons for job changes. One possibility is that individuals at milestone ages are more likely to experience involuntary turnover, potentially due to weaker performance in less fulfilling roles. That said, this interpretation does not contradict our main argument, as lower motivation in misaligned jobs is consistent with a heightened demand for meaning.

has potentially significant costs for employers, yet attracting and retaining better motivated and committed employees can create benefits for both firms and employees. However, changing jobs is only one way individuals can seek meaning during milestone ages and impact firms and markets. In the following section we focus on financial analysts to examine both the robustness and generalizability of these results as well as to test whether individuals change their within-job behaviors in ways that plausibly reflect an increased desire for meaning during milestone ages and the potential market consequences of those changes in behavior.

4 Analysts

4.1 Overview and Sample

In this section we examine whether financial analysts change their forecasting behaviors during milestone ages in a manner consistent with a desire to create meaning. We investigate four outcomes—boldness, accuracy, timeliness, and market impact—that plausibly reflect efforts to create meaning and examine how these forecast characteristics differ when issued by analysts with a milestone age.

We first hypothesize that analysts are more likely to issue bold forecasts during milestone ages. Due to career concerns, it is risky for analysts to issue bold forecasts when they lack superior private information (Hong et al., 2000; Clement and Tse, 2005). Bold forecasts generally reflect analysts' decision to forgo herding in favor of deeper information search and analysis to provide independent insights. Such forecasts have a greater chance of improving the firm's information environment. Second, we hypothesize that analysts will also issue more accurate forecasts during milestone

ages, as more accurate forecasts plausibly reflect a greater effort to understand the firm and create value for their subscribers (Harford et al., 2019; Pope and Wang, 2023). Third, we hypothesize that analysts are more likely to provide timely forecasts following annual earnings announcements during milestone ages. Analysts synthesize new information in earnings announcements, inform their subscribers of the implications for future profitability, and can use those forecasts as a platform for increased engagement with their subscribers. Thus, issuing timely forecasts can reflect both work commitment and efforts to excel, plausibly creating more meaning. Finally, we hypothesize that analyst reports issued during milestone ages generate larger market reactions. Market reactions reflect financial market participants' perceptions of the quality or informativeness of analyst reports, with larger reactions (both positive and negative) reflecting reports that have more likely updated the market's perceptions regarding the firm's underlying value. Thus larger reactions plausibly reflect more meaningful work.

We use three distinct samples to measure analyst activity. Table 3 Panel A1 outlines our first analyst sample that focuses on forecast boldness and accuracy. We use forecasts issued by individual analysts for the years 2001 to 2022 from the China Stock Market and Accounting Research Database (CSMAR) and, for each analyst-firm-year, keep the most recent forecast of year-end earnings issued before the firm's fiscal year-end (December 31 for all Chinese firms listed on the Shenzhen or Shanghai stock exchanges). This approach yields 138,409 analyst-firm-year observations. We retrieve analyst birth years as of July 2015 from SAC and drop observations with missing birth years.⁷ We exclude financial firms (Cheng et al., 2016); firms with stock prices below one yuan or with negative equity (Horton et al., 2017); forecasts before 2005 or after 2021

⁷Due to the availability of birth years, our sample is limited to analysts who were registered with SAC as of July 2015. Robustness tests restricting the sample to only the four years around 2015 show similar results.

due to sparse analyst forecasts; analysts aged below 20 or above 84 (to be consistent with our other samples); forecasts with missing dependent variables; and ages with fewer than 30 observations. Finally, due to our fixed effect structure, we drop firm-years followed by fewer than two analysts and analysts following fewer than two firm-years. The final sample has 52,877 firm-year-analyst observations, covering 11,318 firm-years and 1,396 analysts, with 4.7 analysts per firm-year on average.

Table 3 Panel A2 outlines our second analyst sample that focuses on analysts' responses to earnings announcements. We begin with a sample of 57,804 earnings announcements covering the years 2001 to 2022. Following [deHaan et al. \(2017\)](#), we use two criteria to identify analysts covering those firms: (i) the analyst issued at least one annual earnings forecast for the firm within one year preceding the earnings announcement, and (ii) the analyst issued at least one annual earnings forecast for the firm within one year following the earnings announcement. We only consider forecasts issued by individual analysts rather than by analyst teams to ensure the forecasts in our sample capture individual performance. This procedure yields 17,161 firm announcements and 54,674 firm announcement-analyst observations. We apply the same filters as our first sample (e.g., exclude missing birth years, financial firms, and singletons), resulting in a final sample of 19,710 firm-announcement-analyst observations. These data include 5,962 unique firm announcements and 993 individual analysts. On average, each firm is actively followed by 3.3 analysts, of which 1.8 issue a forecast within the three-day announcement window.

Table 3 Panel A3 outlines our third and final analyst sample that focuses on market reactions to analyst reports. We start with the full sample of 601,442 analyst reports (including solo and team forecasts) from CSMAR and drop all analyst reports for which another analyst report was issued on the same date for the same firm. We then keep the most recent forecast by an individual analyst

of year-end earnings and apply the same filter as our first two samples. We also drop forecasts missing stock returns, and forecasts whose issuance overlaps with the [0,2] earnings announcement window. Our final sample consists of 12,463 firm-year-analyst observations, including 4,872 unique firm-years and 1,129 unique analysts. The average firm-year includes 2.6 analyst reports.

— Table 3 around here —

4.2 Research Design and Summary Statistics

We examine analysts' forecasting behaviors during milestone ages using a modified version of Model (1). The independent variable of interest, *Milestone age*_{*i,t*}, is a dummy variable equal to one if analyst *i* enters an age ending with 9 in year *t*. We include analyst fixed effects to control for all time-invariant analyst characteristics (e.g., education, gender, and experiences before being an analyst), and age cohort fixed effects to mitigate concerns that the effects of milestone ages are confounded by characteristics of certain age groups. We also include firm-year fixed effects to control for firm characteristics that are constant within a given year (e.g., financial performance, disclosure strategies, and information environment). Net of the fixed effect structure, the remaining variations allow us to effectively compare differences in the forecasting behavior of a given analyst during their milestone ages and non-milestone ages, as well as differences between forecasts for a specific earnings announcement by analysts with milestone ages and those without milestone ages.

Using our first analyst sample we create two measures of forecast boldness and a measure of forecast accuracy. *BoldD*_{*i,j,t,d*} is a dummy equal to one if analyst *i*'s one-year-ahead earnings-per-share (EPS) forecast for firm *j* and fiscal year *t* issued on day *d* is more than one standard deviation

from the consensus, and zero otherwise; and $Bold_{i,j,t,d}$, the absolute difference between analyst i 's one-year-ahead EPS forecast for firm j and fiscal year t issued on day d and the consensus, scaled by the absolute value of the consensus. $Accuracy_{i,j,t,d}$ is the absolute difference between analyst i 's one-year-ahead EPS forecast for firm j and fiscal year t issued on day d and the future realized EPS, multiplied by -1 and scaled by the absolute value of the realized EPS. Thus, a higher value of $Accuracy_{i,j,t,d}$ implies higher forecast accuracy. Using the second sample we create $MakeFcast_{i,j,t}$, our measure of analyst activity, which is set equal to one if the analyst i issues an annual EPS forecast within three trading days following firm j 's annual earnings announcement for fiscal year t and zero otherwise. Using the third sample we create $AbsAR_{j,d}$, which is the absolute abnormal return of firm j on day d when the analyst report was issued, multiplied by 100.

Control variables include time-varying analyst characteristics not captured by the analyst fixed effects. All model specifications control for the logarithmic form of analyst age, general experience, All-Star status, and the number of firms that the analyst follows that year. For analyses concerning whether analysts issue forecasts right after earnings announcements, we do not include forecast horizon since some analysts don't issue a forecast in the specified time window. Standard errors are clustered by both analyst and firm-year to correct for correlated residuals over time and within each firm-year.

Table 3 Panel B provides summary statistics for all analyst variables. All continuous variables are winsorized at the 1st and 99th percentiles and are defined in Table A.1. We find that 41.4% of forecasts are “bold,” i.e., more than one standard deviation away from the consensus ($BoldD$). Relative to the consensus, the average forecast has a boldness of 15.1% ($Bold$). $Accuracy$ has a mean value of -0.427 , showing that the average forecast error is 42.7% relative to the realized earnings. The average analyst experience is 16.8 quarters ($Experience$) and the average number

of firms followed is 27.8 (*Firms followed*). The average forecast is issued 215.5 days before the earnings announcement date (122.7 days before the fiscal year end) (*Horizon*), 15.8% of analysts are All-Stars, 55.5% of analysts issue a forecast within days [0, 2] following firms' earnings announcements, and the one-day average absolute abnormal return for analyst report dates is 2.4%. Figure A.1 Panel B shows the distribution of analysts' ages in our sample. Both the mean and median age are 34, although few analysts have milestone ages of 29 or 49; 11% of analyst observations have a milestone age.

4.3 Results

Table 4 presents results for the three analyst samples. Columns 1 through 3 examine characteristics of the most recent forecasts issued before the fiscal year ends. In Column 1 we find that analysts are 4.6% more likely to issue bold forecasts (relative to the unconditional average of 0.414) during milestone ages, compared to the analyst's forecasts during other years as well as compared to other analysts' forecasts in the same year.⁸ In Column 2 we find that analysts' forecasts are on average 3.3% bolder than the average forecast during milestone ages and in Column 3 we find that forecast accuracy is 5.2% higher during milestone ages. Examining the control variables, we find that forecast horizon is positively associated with forecast boldness and negatively associated with forecast accuracy; that All-Stars issue, on average, bolder forecasts; and that more experienced analysts issue less accurate forecasts, consistent with Li et al. (2020).

Column 4 analyzes the likelihood of issuing a forecast within three days following an earnings announcement (*MakeFcast*). We find that analysts are 7.0% more likely to issue a forecast during milestone ages (relative to the unconditional average of 0.555). Analysts who follow more firms

⁸Coefficient estimate of 0.019 divided by the unconditional population average of 0.414.

are also more likely to issue forecasts following an annual earnings announcement. In Column 5 we analyze whether analysts during milestone ages provide incremental information through their reports (e.g., solid analysis and bold forecasts) by examining the stock market reactions. We find that one-day absolute abnormal returns ($AbsAR_{i,j,d}$) are 17.4% higher for reports issued by analysts in milestone ages. Taken together, these findings support our argument that analysts during milestone ages are more engaged in their work and demonstrate high performance, reflecting an increased competence at work. Furthermore, reports issued by analysts with milestone ages generate greater market reactions, suggesting that the analysts' work improves the information environment and provides valuable information to market participants.

— Table 4 around here —

To better understand whether the changes in forecasting behaviors we observe reflect efforts to create meaning, we conduct a cross-sectional test using likely variation in an analyst's "presence of meaning" (POM). As described by [Steger et al. \(2009, page 353\)](#), "POM refers to people's comprehension of their life experiences along with a sense of overarching purpose they are working toward." We hypothesize that individuals with a strong POM are plausibly less likely to search for meaning during milestone ages given the accomplishments they have already achieved. We proxy for high POM using an analyst's All-Star status.

We estimate a modified version of Model (1) which includes an interaction between *Milestone age*_{*i,t*} and *Star analyst*_{*i,t*}. Results are tabulated in Table A.5. We find that the coefficients on *Milestone age*_{*i,t*} remain positive and significant in all columns, suggesting significant changes in behavior for individuals that are *not* All-Stars. In contrast, the interaction term is negative and

significant in Columns 1 and 2, suggesting that All-Star analysts are less likely to change their behaviors during milestone ages. We also test the sum of the coefficients on *Milestone age_{i,t}* and interaction term, and find across all five columns no evidence that All-Star analysts change their behavior during milestone ages (*p*-values tabulated at the bottom of the table).

We also conduct robustness tests, including examining alternative measures of boldness, accuracy, forecast frequency, and absolute abnormal return (Table A.6); more extreme measures of forecast boldness (Table A.7); and a shorter sample period (Table A.8). Our results remain robust.

Overall, the results presented in this section indicate that financial analysts issue bolder, more accurate, and more informative forecasts during milestone ages relative to forecasts issued by the same analyst during non-milestone age years and also relative to forecasts issued for the same forecast period but by analysts without milestone ages. These findings are consistent with analysts' efforts to create meaningful work during periods of heightened demand for meaningfulness that ultimately improve the information environment and create value for investors.

5 Survey

5.1 Overview and Sample

Our tests so far capture professional changes during milestone ages on a broad scale. To complement our archival analysis and better understand individuals' desire to make professional changes during milestone ages and their underlying motivations, we conducted a survey on Prolific.⁹ Participants were required to be between 20 and 84 years old, employed either full- or part-time, reside in

⁹As with all online survey platforms, our sample may not fully reflect the broader labor force. However, prior work has shown Prolific samples to be diverse and reliable for studying attitudinal and behavioral constructs (e.g., Peer et al. 2017).

the United States, and use English as their primary language. 522 qualified individuals consented to participate and completed the survey for \$0.5. After reporting ages and sex and passing an attention check, participants answered questions regarding their desire to make professional changes, including changing jobs, switching roles, pursuing education or training, or approaching their current work differently. Participants who indicated they were either “probably” or “definitely” going to make changes were subsequently asked to rate specific types of professional changes and their reasons. Specifically, we presented these participants with 7 specific types of professional changes they might make and 13 possible reasons for making professional changes developed from studies on work preferences and motivations (Amabile et al., 1994; Steger et al., 2012; De Smet et al., 2022). We classified these 13 reasons into three broad categories, which draws on self-determination theory and prior work on intrinsic motivation (e.g., Amabile et al. 1994 and Deci and Ryan 2000), and distinguishes between meaning-driven, reward-driven, and constraint-driven motivations:

- i) Meaning or purpose driven: desire for greater autonomy in work, better alignment between work and personal strengths, desire to make a greater social impact, seeking more meaning and purpose, and seeking growth;
- ii) Reward driven: promotion or increased compensation, greater flexibility in when and where to work, and desire for more recognition or status;
- iii) External constraints or risks driven: changes in family or life circumstances, health issues, planning to move or relocate, a toxic or unsupportive work environment, and concerns about job security or risk of layoff.

An “Other (please specify)” option was also provided to capture changes or reasons not listed.

We also asked participants to rate the extent to which their current work reflects their values and

their overall work satisfaction. Finally, participants reported their education level, industry of occupation, and range of annual family income before exiting the survey.¹⁰ For our analyses, we excluded 8 individuals who preferred not to report either their education or family income, resulting in a final sample of 514 respondents.

5.2 Research Design and Summary Statistics

To examine individuals' desire to make professional changes during milestone ages, we use a modified version of Model (1), with $ChangeIntent_i$ and $ChangeIntentD_i$ as the primary dependent variables and $Milestone\ age_i$ as our explanatory variable of interest. $ChangeIntent$ is a respondent's self-reported intention to make changes in their professional lives during the current year, ranging from 1 (Definitely not) to 5 (Definitely yes). $ChangeIntentD$ is a dummy variable equal to one if $ChangeIntent$ is 4 or 5. We control for individuals' sex, education, family income, as well as the degree of alignment between their current work and personal values, and their overall work satisfaction. See Table A.1 for detailed definitions. To capture the potentially nonlinear relationship between age and the desire to make professional changes, we include the logarithmic form of a respondent's age.

Table 5 provides summary statistics. $Log(age)$ is winsorized at the 1st and 99th percentiles. 59.5% of respondents answered "Probably yes" or "Definitely yes" when asked about their desire for change ($ChangeIntentD_i$). Figure A.1 Panel C plots the distribution of respondents' ages, which is slightly right-skewed, ranging from 20 to 76, with a mean of 41.7 and a standard deviation of 12.1. In total, 7.6% of respondents have a milestone age. Approximately half of the respondents were female, reported a total annual family income of \$75,000 or more, and felt that their current

¹⁰The survey was conducted in July 2025. See [Survey Questionnaire](#) in the Appendix for the full questionnaire.

work “Mostly” or “Very much so” reflects their values. 61.3% of respondents held a bachelor’s degree and 40.9% reported being “Very satisfied” or “Completely satisfied” with their current work.

— Table 5 around here —

5.3 Results

In Table 6 Panel A Column 1 we analyze $ChangeIntent_i$ and find that individuals with a milestone age express a higher intent of making professional changes (relative to individuals with non-milestone ages). Results are stronger when we include the logarithmic form of age in Column 2 and are robust in Column 3 to controls for demographics, work value alignment, and work satisfaction. In Columns 4 through 6 we analyze $ChangeIntentD_i$ and find that respondents at milestone ages are 21.6 to 23.9 percentage points more likely to report wanting to make a change. The estimated coefficients on $Milestone\ age_i$ are statistically significant at the 1% level and correspond to a 36.3% to 40.2% increase in the likelihood of reporting “Probably yes” or “Definitely yes” relative to the unconditional mean of $ChangeIntentD_i$ (0.595).¹¹ Examining the control variables, we find that both age and work satisfaction are negatively associated with intent to make professional changes. Overall, our findings support the argument that individuals have a stronger desire to make professional changes during milestone ages.

In Table 6 Panel B we examine the motivations for professional changes during milestone ages by focusing on respondents who want to make a change and have a milestone age.¹² Pay/promotion

¹¹Coefficient estimate of 0.216 to 0.239 divided by the unconditional population average of 0.595.

¹²32 respondents considering or making changes at milestone ages, including 4 at age 29, 17 at 39, 7 at 49, 3 at 59, and 1 at 69. Although the number of milestone-aged respondents considering a change is modest, the patterns are consistent and informative.

is the top-cited reason, and meaning-related motivations rank consistently high among the top two or three—well above reactive motivations. This is consistent with our argument that pursuit of meaning at work plays a significant role in driving professional changes during milestone ages. In Table 6 Panel C we present ranking of types of changes being considered. We find that individuals at milestone ages consider making changes by (i) changing how they approach their current work, (ii) switching to a different employer, and (iii) taking on a new role at their current employer.

Overall, we find that individuals at milestone ages are more likely to consider making professional changes, and a significant motive for these changes is a search for meaning. These findings are consistent with individuals' efforts to create meaning during milestone ages by changing their professional behaviors.

— Table 6 around here —

6 Cross-Setting Robustness Tests

Beyond the robustness checks tailored to individual settings (Tables A.2 through A.8), we conduct additional analyses across settings. To address concerns that ages ending in other digits might yield similar results, we repeat our analyses for ages ending in 0–8. Table A.9 summarizes 20 estimations across the analyst and LinkedIn settings, replacing *Milestone age_{i,t}* with indicators for ages ending in each digit from 0 to 8 (*X-ending age*). We include the milestone-age results for completeness in the first row. No significant changes appear for analysts at ages ending in digits other than 9. In the LinkedIn setting, employees are also more likely to quit at ages ending in 0 or 1, possibly reflecting delayed job changes planned at milestone ages or noise in inferred ages from

high school graduation years. These findings highlight the value of multiple settings for examining changes in professional behavior at milestone ages.

7 Conclusion

We study whether demand for meaning, a non-pecuniary motive, affects human capital and information production in capital markets. Using milestone ages as a predictable, time-varying shock to introspection, we show that heightened demand for meaning is associated with labor market reallocation and analyst information production. Individuals at milestone ages are more likely to quit jobs, start new positions, relocate internationally, and move into lower-seniority or lower-compensation roles. Within financial professions, financial analysts at milestone ages exert greater effort, issue bolder and more accurate forecasts, and their forecasts elicit larger market reactions. Survey evidence supports value alignment and purpose-seeking as the underlying motives.

Our findings contribute to the finance literature in three ways. First, they add to research on capital-market information production by showing that non-pecuniary motives help explain variation in analyst effort, independence, and forecast informativeness. Second, they contribute to the literature on agency frictions and human capital by suggesting that demand for meaning can complement monetary incentives where career concerns and incomplete contracting are salient. Third, they contribute to behavioral finance by linking temporal landmarks and life-cycle introspection to economically relevant labor-market choices and forecasting behavior in capital markets.

More broadly, the evidence suggests that capital markets may be shaped not only by formal contracts and pecuniary incentives, but also by predictable variation in non-pecuniary motives. This

perspective is particularly relevant in labor markets and financial occupations where discretionary effort, independent judgment, and value alignment are difficult to contract on.

Several caveats are worth highlighting. Our analyses rely on the assumption that search for meaning intensifies during milestone ages. In the LinkedIn setting, age is inferred from high school graduation dates, which may introduce measurement error. Although we examine two distinct settings, the observed behaviors may not capture all professional changes associated with the search for meaning at work. Future research can further disentangle underlying mechanisms and examine whether similar effects arise in other capital market settings.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT in order to improve the writing clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability

The data used in this project are subject to a confidentiality agreement and cannot be shared.

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Tables

Table 1: LinkedIn User Descriptive Statistics

This table provides an overview of the LinkedIn sample. Panel A presents our sample selection criteria and Panel B provides summary statistics of variables used in the analyses. The initial panel consists of LinkedIn users who list a single high school they attended for exactly three or four years and the corresponding dates of attendance. We construct a panel data set of these individuals' work histories (based on position at the end of the year) covering the years 1951 through 2023. All dummy variables are set equal to one if the condition is met and equal to zero otherwise. *New job* is a dummy variable equal to one for the first year an employee works in a new company. *Job quit*, *Switch country*, and *Switch role* are dummy variables equal to one for the last year an employee works in a company, a country, and a job category, respectively. *Lower seniority* and *Lower salary* are dummy variables equal to one if an employee leaves a company for a new job with lower seniority or salary, respectively. *Prosocial job* is a dummy variable equal to one if an employee leaves a company and switches from a non-prosocial job to a prosocial job. *Milestone age* is a dummy variable equal to one for the years an employee enters an age ending with 9. *Age* is the age of employee and $\text{Log}(\text{age})$ is the logarithmic form; Seniority_{t-1} is the seniority of an employee's position in the previous year and ranges within our sample from 1 (entry-level/intern) to 4 (manager). Tenure_{t-1} is the number of years that an employee has worked in their position as of the previous year and $\text{Log}(\text{tenure}_{t-1})$ is the logarithmic form. All continuous variables are winsorized at the 1st and 99th percentiles. See Table A.1 for detailed variable definitions.

<i>Panel A: Sample selection</i>	
	<i>Observations</i>
Individual-years (aged 18 to 84)	8,768,846
Less: individuals starting jobs at least three years before graduation	(252,845)
Less: missing historical role or location for at least four years	(1,366,232)
Less: ages less than 20	(235,932)
Sample before multivariate analyses	6,913,837
Less: ages with less than 30 observations	(50)
Less: singleton individuals or country-year-roles	(194,545)
Individual-year sample (<i>New job</i>)	6,719,242
Less: missing <i>Job quit</i> , <i>Switch country</i> , <i>Switch role</i> , or <i>Lower seniority</i>	(655,146)
Less: ages with fewer than 30 observations	(48)
Less: singleton individuals or country-year-roles	(60,754)
Main individual-year sample (<i>Job quit</i>, <i>Switch country</i>, <i>Switch role</i>, <i>Lower seniority</i>)	6,003,294
Unique individuals	615,558
Unique companies	701,246
Unique countries	195
Unique roles	150

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Table 1: LinkedIn User Descriptive Statistics (*Continued*)

<i>Panel B: Summary statistics</i>						
	N	Mean	SD	<i>Distribution</i>		
				10 th Pctl	Median	90 th Pctl
New job	6,719,242	0.2440	0.4295	0.0000	0.0000	1.0000
Job quit	6,003,294	0.2460	0.4307	0.0000	0.0000	1.0000
Switch country	6,003,294	0.0198	0.1393	0.0000	0.0000	0.0000
Switch role	6,003,294	0.1982	0.3986	0.0000	0.0000	1.0000
Lower seniority	6,003,294	0.0534	0.2248	0.0000	0.0000	0.0000
Lower salary	5,784,625	0.0802	0.2717	0.0000	0.0000	0.0000
Prosocial job	5,775,497	0.0229	0.1496	0.0000	0.0000	0.0000
Milestone age	6,003,294	0.0764	0.2657	0.0000	0.0000	0.0000
Log(age)	6,003,294	3.4145	0.2711	3.0910	3.3673	3.8067
Age	6,003,294	31.6072	9.1942	22.0000	29.0000	45.0000
Seniority _{t-1}	6,003,294	2.0034	0.8927	1.0000	2.0000	3.0000
Log(tenure _{t-1})	6,003,294	0.8569	0.8409	0.0000	0.6931	2.0794
Tenure _{t-1}	6,003,294	2.5217	3.8636	0.0000	1.0000	7.0000

Table 2: Milestone Ages and Job Changes

This table analyzes employment changes during milestone ages within the LinkedIn user sample. The dependent variables in Columns 1 through 7 are, respectively, *New job*, *Job quit*, *Switch country*, *Switch role*, *Lower seniority*, *Lower salary*, and *Prosocial job*. The explanatory variable of interest is *Milestone age*. We include as controls $\text{Log}(\text{age})$ and $\text{Log}(\text{tenure}_{t-1})$, and in some specifications Seniority_{t-1} . We also include employee, country-year-role, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by employee are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

$$\text{Employment Change}_{i,t} = \beta_0 + \beta_1 \text{Milestone age}_{i,t} + \sum \beta_{k1} \text{Controls}_{i,t} + \sum \beta_{k2} \text{Employee}_i + \sum \beta_{k3} \text{Country} \times \text{Year} \times \text{Role}_{c,t,r} + \sum \beta_{k4} \text{Cohort}_{i,t} + \epsilon_{i,t}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New job	Job quit	Switch country	Switch role	Lower seniority	Lower salary	Prosocial job
Milestone age	0.0013** (0.0006)	0.0018*** (0.0006)	0.0004** (0.0002)	-0.0004 (0.0006)	0.0007** (0.0004)	0.0007* (0.0004)	0.0004* (0.0002)
Log(age)	-0.5064*** (0.0096)	-0.6416*** (0.0106)	-0.0479*** (0.0030)	-0.3771*** (0.0096)	-0.1361*** (0.0056)	-0.2170*** (0.0068)	-0.0694*** (0.0038)
Seniority _{t-1}	-0.0350*** (0.0003)	-0.0220*** (0.0003)	-0.0008*** (0.0001)	-0.0161*** (0.0003)			-0.0026*** (0.0001)
Log(tenure _{t-1})	0.0731*** (0.0003)	0.0636*** (0.0003)	0.0045*** (0.0001)	0.0521*** (0.0003)	0.0154*** (0.0002)	0.0176*** (0.0002)	0.0053*** (0.0001)
Observations	6,719,242	6,003,294	6,003,294	6,003,294	6,003,294	5,784,625	5,775,497
Adj. R ²	0.1179	0.0978	0.1940	0.1152	0.0257	0.0664	0.0689
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year × Role FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Analyst Descriptive Statistics

This table provides an overview of the analyst sample covering the years 2005 through 2021. Panel A1 presents the selection criteria for our sample of annual forecasts where we keep each analyst's most recent forecasts issued before the fiscal year ends and with a horizon of one year or less. Panel A2 presents the selection criteria for our sample of analyst responses to annual earnings announcements. To avoid characterizing previously dropped coverage as inactivity, we require the initial sample to only include analysts who issue at least one annual earnings forecast within one year, both before and after the annual earnings announcements. Panel A3 presents the selection criteria for our sample of stock market reactions to analyst reports. Panel B shows the summary statistics of the variables used in our tests. All dummy variables are set equal to one if the condition is met and equal to zero otherwise. *BoldD* is a dummy variable equal to one if an analyst's most recent forecast is more than one standard deviation away from the consensus. *Bold* is the absolute difference between an analyst's most recent forecast and the consensus, scaled by the absolute consensus. *Accuracy* is the absolute difference between the analyst's most recent earnings forecast and the future realized earnings, scaled by the absolute realized earnings and multiplied by -1 . *Milestone age* is a dummy variable equal to one for the years an analyst enters an age ending with 9. *MakeFcast* is a dummy variable equal to one if an analyst issues a forecast over trading days $[0, 2]$ of an annual earnings announcement for the fiscal year t , $t + 1$, or $t + 2$. *AbsAR* is the one-day absolute abnormal return calculated as the firm's daily stock return adjusted by value-weighted market return on the day an analyst report is issued, multiplied by 100. *Age* is the age of an analyst; *Experience* is the number of quarters since an analyst issued the first earnings forecast; *Firms followed* is the number of firms an analyst follows in a year; *Horizon* is the number of days between the forecast date and the corresponding firm's earnings announcement date; *Log(age)*, *Log(experience)*, *Log(Firms followed)*, and *Log(horizon)* are their logarithmic forms, respectively; *Star analyst* is a dummy variable equal to one if an analyst is ranked as All-star. All continuous variables are winsorized at the 1st and 99th percentiles. See Table A.1 for detailed variable definitions.

Panel A1: Analysts' forecast characteristics

	<i>Observations</i>
Solo forecasts	961,041
Less: forecasts with horizon of greater than one year or issued after fiscal year-ends	(717,278)
Less: not the forecasts closest to fiscal year-ends	(105,354)
Less: missing analyst birth year	(70,790)
Less: financial industry	(3,014)
Less: firms with stock price below one yuan or negative equity at fiscal year-ends	(23)
Less: years before 2005 or after 2021	(246)
Less: ages out of 20 to 84	(44)
Less: missing dependent variables	(7,044)
Less: ages with fewer than 30 observations	(103)
Less: singleton firm-year or analysts	(4,268)
Final firm-year-analyst sample	52,877
Unique firm-years	11,318
Unique analysts	1,396
Average number of analysts per firm-year	4.7

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Table 3: Analyst Descriptive Statistics (*Continued*)

<i>Panel A2: Analysts' response to earnings announcements</i>	
	<i>Observations</i>
Firm-announcements	57,804
Firm-announcements with active analyst following	17,161
Firm-announcement-analyst observations	54,674
Less: missing analyst birth year	(26,860)
Less: financial industry	(1,420)
Less: firms with stock price below one yuan or negative net asset at fiscal year-end	(8)
Less: years before 2005 or after 2021	(684)
Less: ages out of 20 to 84	(10)
Less: missing control variables	(95)
Less: ages with fewer than 30 observations	(136)
Less: singleton firm-announcements or analysts	(5,751)
Final firm-announcement-analyst sample	19,710
Unique firm-announcements	5,962
Unique analysts	993
Average analysts per firm-announcement	3.3
<i>Panel A3: Market reaction to analyst reports</i>	
	<i>Observations</i>
Unique analyst reports	601,442
Less: reports for the same firm and on the same date	(324,771)
Less: missing analyst birth year	(196,025)
Less: missing stock returns	(4,241)
Less: reports overlapped with earnings announcements window [0, 2]	(18,442)
Less: not the reports closest to fiscal year-ends	(36,667)
Less: financial industry	(537)
Less: firms with stock price below one yuan or negative net asset at fiscal year-end	(14)
Less: years before 2005 or after 2021	(159)
Less: ages out of 20 to 84	(10)
Less: ages with fewer than 30 observations	(74)
Less: singleton firm-announcements or analysts	(8,039)
Final firm-year-analyst sample	12,463
Unique firm-years	4,872
Unique analysts	1,129
Average analysts per firm-year	2.6

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Table 3: Analyst Descriptive Statistics (*Continued*)

<i>Panel B: Summary statistics</i>						
	N	Mean	SD	<i>Distribution</i>		
				10 th Pctl	Median	90 th Pctl
BoldD	52,877	0.414	0.493	0.000	0.000	1.000
Bold	52,877	0.151	0.184	0.012	0.082	0.385
Accuracy	52,877	-0.427	0.992	-0.939	-0.135	-0.019
Milestone age	52,877	0.110	0.312	0.000	0.000	1.000
Log(age)	52,877	3.536	0.146	3.367	3.526	3.738
Age	52,877	34.707	5.283	29.000	34.000	42.000
Log(experience)	52,877	2.485	0.920	1.156	2.643	3.524
Experience	52,877	16.778	12.200	3.178	14.056	33.922
Log(firms followed)	52,877	2.953	0.863	1.946	2.944	3.989
Firms followed	52,877	27.772	28.539	7.000	19.000	54.000
Log(horizon)	52,877	5.314	0.362	4.852	5.342	5.835
Horizon	52,877	215.500	76.267	127.000	208.000	341.000
Star analyst	52,877	0.158	0.364	0.000	0.000	1.000
MakeFcast	19,710	0.555	0.497	0.000	1.000	1.000
AbsAR	12,463	2.354	3.583	0.240	1.399	5.210

Table 4: Milestone Ages and Analyst Forecasting

This table analyzes changes in forecasting behaviors during milestone ages within the Chinese analyst sample. In Columns 1 to 3 we analyze the forecast characteristics *BoldD*, *Bold*, and *Accuracy* for analysts' most recent forecasts before the fiscal year ends. In Column 4 we analyze *MakeFcast* and in Column 5 we analyze *AbsAR*. The explanatory variable of interest is *Milestone age*. We include as controls *Log(age)*, *Log(experience)*, *Log(Firms followed)*, and *Star analyst*, and in some specifications *Log(horizon)*. We also include analyst, firm-year, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by the analyst and firm-year are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

$$\text{Forecasting Behavior}_{i,j,t} = \beta_0 + \beta_1 \text{Milestone age}_{i,t} + \sum \beta_{k1} \text{Controls}_{i,j,t} + \sum \beta_{k2} \text{Analyst}_i + \sum \beta_{k3} \text{Firm} \times \text{Year}_{j,t} + \sum \beta_{k4} \text{Cohort}_{i,t} + \epsilon_{i,j,t}$$

	(1) BoldD	(2) Bold	(3) Accuracy	(4) MakeFcast	(5) AbsAR
Milestone age	0.019** (0.009)	0.005** (0.003)	0.022*** (0.008)	0.039** (0.019)	0.409** (0.161)
Log(age)	0.566 (0.379)	-0.001 (0.120)	-0.261 (0.352)	0.371 (1.027)	-3.312 (7.332)
Log(experience)	0.002 (0.008)	0.001 (0.002)	-0.014** (0.007)	0.050 (0.033)	0.020 (0.107)
Log(firms followed)	0.002 (0.005)	0.001 (0.001)	0.011** (0.005)	0.060*** (0.012)	0.095 (0.070)
Log(horizon)	0.027*** (0.009)	0.014*** (0.003)	-0.404*** (0.013)		0.706*** (0.103)
Star analyst	0.022** (0.010)	0.007** (0.003)	0.003 (0.012)	0.007 (0.020)	-0.081 (0.148)
Observations	52,877	52,877	52,877	19,710	12,463
Adj. R^2	0.094	0.508	0.802	0.124	0.274
Analyst FE	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Table 5: Survey Respondent Descriptive Statistics

This table presents the summary statistics for the variables used in the survey respondent sample. Respondents were recruited on Prolific and met the following criteria at the time of the survey: aged 20 to 84, employed either full- or part-time, residing in the US, and primarily using English. The initial sample consists of 522 respondents. For our analyses, we exclude 8 individuals who did not report their education or family income, resulting in a final sample of 514 respondents. *ChangeIntent* is a respondent's self-reported intention to make a change in their professional life during the current year, ranging from 1 (Definitely not) to 5 (Definitely yes). This includes planning, seriously considering, or having recently made changes, such as switching jobs, changing roles, pursuing education or training, or approaching work differently. *ChangeIntentD* is a dummy variable equal to one if *ChangeIntent* is 4 or 5. *Age* is a respondent's reported age and $\text{Log}(\text{age})$ is its natural logarithm, winsorized at the 1st and 99th percentiles. *Milestone age* is a dummy variable for respondents whose reported age ends with 9; *Sex* is a dummy variable for female respondents; *Bachelor's degree* is a dummy variable for respondents who holds a bachelor's degree; *Family income* is a dummy variable for respondents with total annual family income of \$75,000 or more; *Value alignment* is a dummy variable for respondents who feel their current work "Mostly" or "Very" reflects their values; *Work satisfaction* is a dummy variable for respondents who are "Very satisfied" or "Completely satisfied" with their current work. All dummy variables are set equal to one if the condition is met and zero otherwise. See Table A.1 for detailed variable definitions.

	N	Mean	SD	Distribution		
				10 th Pctl	Median	90 th Pctl
ChangeIntent	514	3.436	1.354	1.000	4.000	5.000
ChangeIntentD	514	0.595	0.491	0.000	1.000	1.000
Milestone age	514	0.076	0.265	0.000	0.000	0.000
Log(age)	514	3.689	0.293	3.258	3.689	4.060
Age	514	41.733	12.106	26.000	40.000	58.000
Sex	514	0.516	0.500	0.000	1.000	1.000
Bachelor's degree	514	0.613	0.488	0.000	1.000	1.000
Family income	514	0.516	0.500	0.000	1.000	1.000
Value alignment	514	0.516	0.500	0.000	1.000	1.000
Work satisfaction	514	0.409	0.492	0.000	0.000	1.000

Table 6: Milestone Ages and Career Change Intentions

This table analyzes survey respondents' intentions to make changes in their professional lives. Panel A examines whether respondents have a stronger intention to make changes at milestone ages. Panel B presents 13 reasons for changes among respondents considering or making changes at milestone ages, ranked by their average importance scores ranging from 1 to 7, with 1 labeled "Not at all important," 4 labeled "Moderately important," and 7 labeled "Extremely important." Panel C presents 7 specific professional changes ranked by their average relevance scores ranging from 1 (Not at all) to 7 (Extremely) among the same group of respondents. In panel A, dependent variables are *ChangeIntent* in Columns 1 to 3 and *ChangeIntentD* in Columns 4 to 6. *ChangeIntent* is a respondent's self-reported intention to make a change in their professional life during the current year, ranging from 1 (Definitely not) to 5 (Definitely yes). This includes planning, seriously considering, or having recently made changes, such as switching jobs, changing roles, pursuing education or training, or approaching work differently. *ChangeIntentD* is a dummy variable equal to one if *ChangeIntent* is 4 or 5, and zero otherwise. The explanatory variable of interest is *Milestone age*. See Table A.1 for detailed variable definitions. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

$$\text{Career Change Intent}_i = \beta_0 + \beta_1 \text{Milestone age}_i + \sum \beta_{k1} \text{Controls}_i + \epsilon_i$$

Panel A: Professional change intent						
	(1) ChangeIntent	(2) ChangeIntent	(3) ChangeIntent	(4) ChangeIntentD	(5) ChangeIntentD	(6) ChangeIntentD
Milestone age	0.389* (0.225)	0.457** (0.223)	0.407* (0.212)	0.216*** (0.081)	0.239*** (0.081)	0.220*** (0.077)
Log(age)		-0.776*** (0.202)	-0.656*** (0.193)		-0.257*** (0.073)	-0.216*** (0.070)
Sex			0.061 (0.113)			-0.007 (0.041)
Bachelor's degree			-0.134 (0.122)			-0.038 (0.044)
Family income			-0.120 (0.119)			-0.036 (0.043)
Value alignment			-0.090 (0.144)			-0.000 (0.052)
Work satisfaction			-0.758*** (0.145)			-0.294*** (0.053)
Constant	3.406*** (0.062)	6.266*** (0.746)	6.295*** (0.715)	0.579*** (0.022)	1.525*** (0.270)	1.543*** (0.260)
Observations	514	514	514	514	514	514
Adj. R ²	0.004	0.030	0.122	0.012	0.033	0.119

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Table 6: Milestone Ages and Career Change Intentions (*Continued*)

<i>Panel B: Rank of reasons of changes for respondents with a milestone age (n=32)</i>				
Rank	Reasons for Change	Construct	Mean	Median
1	Promotion or increased compensation	Reward-driven motivation	4.969	5
2	Better alignment between work and strengths	Meaning-driven motivation	4.250	4
3	Seeking more meaning and purpose in work	Meaning-driven motivation	4.188	4
4	Desire more flexibility in when and where you work	Reward-driven motivation	4.156	4.5
5	Seeking growth	Meaning-driven motivation	4.031	4
6	Desire for greater autonomy in work	Meaning-driven motivation	3.906	4
7	Concern about job security or risk of layoff	Constraint-driven	3.500	3
8	Desire to make a greater social impact	Meaning-driven motivation	3.438	3
9	Changes in family or life circumstances	Constraint-driven	3.188	3
10	Desire for more recognition or status	Reward-driven motivation	3.000	3
11	Toxic or unsupportive work environment	Constraint-driven	2.531	1.5
12	Planning to move or relocate	Constraint-driven	2.281	1
13	Health issues	Constraint-driven	2.094	1
<i>Panel C: Rank of professional changes for respondents with a milestone age (n=32)</i>				
Rank	Professional Changes		Mean	Median
1	Changing how you approach current work		4.000	4
2	Switching to a different employer		3.781	4
3	Taking on a new role at your current employer		3.781	4
4	Pursuing more education or training		3.469	3.5
5	Switching to a different field or industry		2.938	2
6	Starting your own business or freelancing		2.531	1
7	Taking a break or stepping away from the workforce		2.125	2

Appendix

Table A.1: Variable Definition

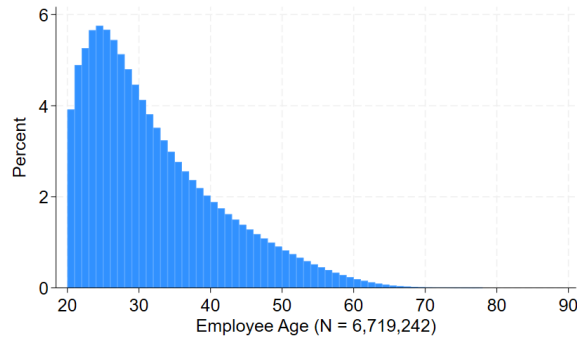
Variable	Definition
LinkedIn Users	
$Age_{i,t}$	Age of individual i in year t (i.e., year t minus birth year). Birth year is inferred from the year when individual i graduated from high school in 18.
$Cohort_{i,t}$	Age decades centering around each milestone age. Decades include ages 15 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74, and 75 to 84, respectively.
$Job\ quit_{i,t}$	Dummy variable equal to one if individual i leaves a company in year t .
$Lower\ salary_{i,t}$	Dummy variable equal to one if individual i leaves a company in year t and takes a new job with lower salary. <i>Revelio</i> estimates the salary for each position based on role, seniority, company, and country using a regression-based model.
$Lower\ seniority_{i,t}$	Dummy variable equal to one if individual i leaves a company in year t and takes a new job with lower seniority.
$Milestone\ age_{i,t}$	Dummy variable equal to one if individual i enters an age ending with 9 in year t .
$New\ job_{i,t}$	Dummy variable equal to one if individual i joins a new company in year t .
$Prosocial\ job_{i,t}$	Dummy variable equal to one if individual i leaves a company and switches from a non-prosocial job to a prosocial job. We follow Burbano et al. (2024) to construct a prosocial (beneficence) rating and define prosocial jobs as O*NET occupations that have a prosocial rating above the 75 th percentile.
$Seniority_{i,t-1}$	Seniority of individual i 's job as of year $t - 1$. <i>Revelio</i> predicts seniority using an individual's job title, company, industry, age, previous seniority, and position history. The numerical value ranges from 1 (entry-level/intern) to 4 (manager).
$Switch\ country_{i,t}$	Dummy variable equal to one if year t is the last year individual i works in a country.
$Switch\ role_{i,t}$	Dummy variable equal to one if year t is the last year individual i stays in a job category (role). There are 150 job categories in total.
$Tenure_{i,t-1}$	The number of years that individual i has worked in their position as of year $t - 1$.
$X\text{-ending}\ age_{i,t}$	Dummy variable equal to one if individual i enters an age ending with X in year t .
Analysts	
$AbsAR_{i,j,t}$	Absolute abnormal return. The one-day absolute abnormal return is calculated as the absolute difference between the firm's daily stock return and the value-weighted market return on the day analyst i issues a report with the most recent forecast for firm j before the end of fiscal year t , multiplied by 100.
$Accuracy_{i,j,t}$	Forecast accuracy. The absolute difference between analyst i 's EPS forecast for firm j and year t and the future realized EPS, scaled by the absolute realized earnings, multiplied by -1 . The sample is restricted to the most recent forecasts before the fiscal year ends and within one year before the earnings announcements.
$Age_{i,t}$	Age of analyst i in year t (i.e., year t minus birth year).

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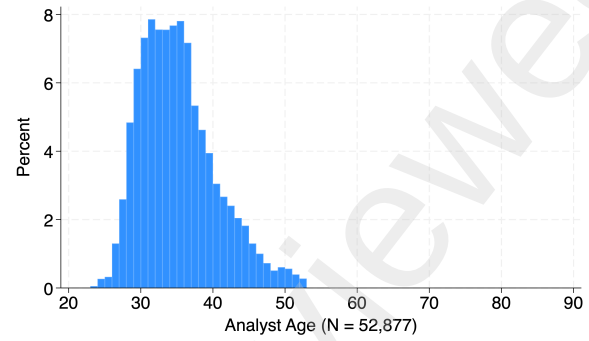
Table A.1 Variable Definition (*Continued*)

Variable	Definition
$Bold_{i,j,t}$	Forecast boldness. The absolute difference between analyst i 's EPS forecast for firm j and year t and the consensus, scaled by the absolute consensus. The sample is restricted to the most recent forecasts before fiscal year-end and within one year before the corresponding earnings announcements. The consensus is the mean of other analysts' forecasts for firm j and year t . We require the consensus to be within 180 days and based on a minimum of two individual analyst estimates.
$BoldD_{i,j,t}$	Forecast boldness. Dummy variable equal to one if analyst i 's EPS forecast for firm j in year t is more than one standard deviation away from the most recent consensus.
$Cohort_{i,t}$	Age decades centering around each milestone age. Decades include ages 15 to 24, 25 to 34, 35 to 44, and 45 to 54, respectively.
$Experience_{i,t}$	Number of quarters since analyst i issues the first forecast up to the end of year t .
$Firms\ followed_{i,t}$	Number of firms analyst i follows in year t . We use the natural log form in analyses.
$Horizon_{i,j,t,d}$	Number of days between the date d analyst i issues forecast for firm j in year t and the corresponding firm's earnings announcement date.
$MakeFcast_{i,j,t}$	Dummy variable equal to one if analyst i issues an annual EPS forecast within trading days $[0, 2]$ of firm j 's earnings announcement for fiscal year t , $t + 1$, or $t + 2$.
$Milestone\ age_{i,t}$	Dummy variable equal to one if analyst i enters an age ending with 9 in year t .
$Star\ analyst_{i,t-1}$	Dummy variable equal to one if the analyst i is ranked as a star by the <i>New Fortune Magazine</i> in year $t - 1$.
Survey	
Age_i	Respondent i 's reported age and we use $Log(age)$ in our analyses.
$Bachelor's\ degree_i$	Dummy variable equal to one if respondent i holds a bachelor's degree.
$ChangeIntent_i$	Respondent i 's self-reported intention to make a change in their professional life as of the survey year, ranging from 1 (Definitely not) to 5 (Definitely yes). This includes planning, seriously considering, or having recently made changes, such as switching jobs, changing roles, pursuing education or training, or approaching work differently.
$ChangeIntentD_i$	Dummy variable equal to one if $ChangeIntent$ is 4 or 5.
$Family\ income_i$	Dummy variable equal to one if total annual family income is \$75,000 or more.
Sex_i	Dummy variable equal to one if respondent i is female.
$Value\ alignment_i$	Dummy variable equal to one if respondent i feels her/his current work "Mostly" or "Very" reflects her/his values.
$Work\ satisfaction_i$	Dummy variable equal to one if respondent i is "Very satisfied" or "Completely satisfied" with her/his current work.

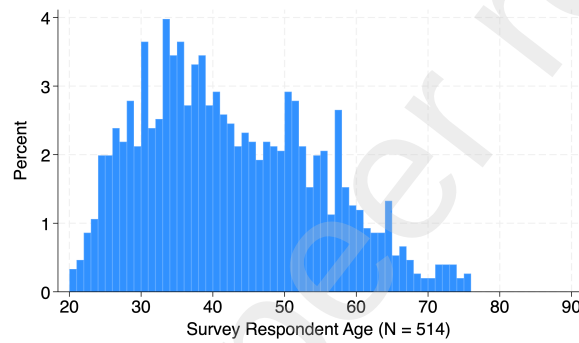
Figure A.1: Age Distribution across Settings



Panel A LinkedIn Users' Ages



Panel B Analysts' Ages



Panel C Survey Respondents' Ages

This figure shows the distribution of individuals' ages across three settings based on the samples for our main analyses. All histograms use a bin width of 1, and the y-axis represents percentage. Panel A presents the distribution of LinkedIn users' ages ranging from 20 to 78. Panel B presents the distribution of financial analysts' ages ranging from 23 to 53. Panel C presents the distribution of survey respondents' ages ranging from 20 to 76.

Table A.2: Milestone Ages and Job Changes: Alternative Fixed Effects

This table analyzes employment changes during milestone ages within the LinkedIn user sample and includes an alternative fixed effect structure. The dependent variables in Columns 1 through 7 are, respectively, *New job*, *Job quit*, *Switch country*, *Switch role*, *Lower seniority*, *Lower salary*, and *Prosocial job*. The explanatory variable of interest is *Milestone age*. The coefficients on the constant term and the same set of control variables in Table 2 are not presented for brevity. We include employee, age cohort, year, job role, and country fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by employee are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New job	Job quit	Switch country	Switch role	Lower seniority	Lower salary	Prosocial job
Milestone age	0.0012** (0.0006)	0.0015** (0.0006)	0.0003 (0.0002)	-0.0004 (0.0006)	0.0007* (0.0003)	0.0006 (0.0004)	0.0004* (0.0002)
Observations	6,823,466	6,103,613	6,103,613	6,103,613	6,103,613	5,882,728	5,875,247
Adj. R^2	0.1098	0.0908	0.1339	0.1076	0.0214	0.0646	0.0631
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Role FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3: Milestone Ages and Job Changes: Macroeconomic Uncertainty

This table analyzes whether the employment changes during milestone ages vary with macroeconomic uncertainty within the LinkedIn user sample. The dependent variable is *Job quit*. The proxies for *High uncertainty* are as follows. *Return volatility* is a dummy variable equal to one for years with a volatility of daily market returns above the 80th percentile. *GDP fcast dispersion* is a dummy variable equal to one for years with dispersion in the gross domestic product (GDP) forecasts issued by the Society of Professional Forecasters above the 80th percentile, available from 1969 to 2023. *VIX* is a dummy variable equal to one for years with a Chicago Board Options Exchange Volatility Index above the 80th percentile, available from 1990 to 2023. *Covid19* is a dummy variable equal to one for years from 2020 to 2022. The explanatory variables of interest are *Milestone age* $\times$ *High uncertainty*, the interaction terms of *Milestone age*, and one of the proxies for *High uncertainty*. The coefficients on the constant term and the same set of control variables in Table 2 are not presented for brevity. We include employee, country-year-role, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by employee are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

$$\begin{aligned} \text{Employment Change}_{i,t} = & \beta_0 + \beta_1 \text{Milestone age}_{i,t} + \beta_2 \text{Milestone age}_{i,t} \times \text{High uncertainty}_t \\ & + \sum \beta_{k1} \text{Controls}_{i,t} + \sum \beta_{k2} \text{Employee}_i + \sum \beta_{k3} \text{Country} \times \text{Year} \times \text{Role}_{c,t,r} \\ & + \sum \beta_{k4} \text{Cohort}_{i,t} + \epsilon_{i,t} \end{aligned}$$

	(1)	(2)	(3)	(4)
	Job quit	Job quit	Job quit	Job quit
Milestone age	0.0010 (0.0007)	-0.0003 (0.0007)	0.0009 (0.0007)	0.0004 (0.0006)
Milestone age $\times$ Return volatility	0.0048*** (0.0017)			
Milestone age $\times$ GDP fcast dispersion		0.0113*** (0.0017)		
Milestone age $\times$ VIX			0.0041** (0.0016)	
Milestone age $\times$ Covid19				0.0188*** (0.0030)
Observations	6,003,294	6,001,936	5,832,117	6,003,294
Adj. R^2	0.0978	0.0978	0.0933	0.0978
Controls	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes
Country $\times$ Year $\times$ Role FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Table A.4: Milestone Ages and Job Changes: Macroeconomic Uncertainty—Narrow Window

This table analyzes whether the employment changes during milestone ages vary with macroeconomic uncertainty in the subsample of ages ending in 7, 8, 9, 0, and 1. The dependent variable is *Job quit*. The proxies for *High uncertainty* are as follows. *Return volatility* is a dummy variable equal to one for years with a volatility of daily market returns above the 80th percentile. *GDP fcast dispersion* is a dummy variable equal to one for years with dispersion in the gross domestic product (GDP) forecasts issued by the Society of Professional Forecasters above the 80th percentile, available from 1969 to 2023. *VIX* is a dummy variable equal to one for years with a Chicago Board Options Exchange Volatility Index above the 80th percentile, available from 1990 to 2023. *Covid19* is a dummy variable equal to one for years from 2020 to 2022. The explanatory variables of interest are *Milestone age* $\times$ *High uncertainty*, the interaction terms of *Milestone age*, and one of the proxies for *High uncertainty*. The coefficients on the constant term and the same set of control variables in Table 2 are not presented for brevity. We include employee, country-year-role, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by employee are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

	(1) Job quit	(2) Job quit	(3) Job quit	(4) Job quit
Milestone age	0.0023*** (0.0007)	0.0015** (0.0007)	0.0025*** (0.0008)	0.0018*** (0.0007)
Milestone age $\times$ Return volatility	0.0033* (0.0019)			
Milestone age $\times$ GDP fcast dispersion		0.0080*** (0.0019)		
Milestone age $\times$ VIX			0.0021 (0.0018)	
Milestone age $\times$ Covid19				0.0156*** (0.0033)
Observations	2,738,036	2,737,499	2,660,640	2,738,036
Adj. R^2	0.1255	0.1255	0.1202	0.1255
Controls	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes
Country $\times$ Year $\times$ Role FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Table A.5: Milestone Ages and Analyst Forecasting: All-Star Analysts

This table analyzes changes in forecasting behaviors during milestone ages, moderated by the All-Star analyst status. In Columns 1 to 3 we analyze the forecast characteristics *BoldD*, *Bold*, and *Accuracy* for analysts' most recent forecasts before the fiscal year ends. In Column 4 we analyze *MakeFcast* and in Column 5 we analyze *AbsAR*. The explanatory variable of interest is *Milestone age* $\times$ *Star analyst*, an interaction term of *Milestone age* and *Star analyst*. *Star analyst* is a dummy variable equal to one if an analyst is voted as an All-Star analyst. Coefficients on the constant term and other control variables in Table 4 are not presented for brevity. We include analyst, firm-year, and age cohort fixed effects. We tabulate the *p*-value for *F*-tests that the sum of coefficients on *Milestone age* and *Milestone age* $\times$ *Star analyst* equals zero at the bottom of this table. See Table A.1 for detailed variable definitions. Standard errors clustered by the analyst and firm-year are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

$$\begin{aligned} \text{Forecasting Behavior}_{i,j,t} = & \beta_0 + \beta_1 \text{Milestone age}_{i,t} + \beta_2 \text{Milestone age} \times \text{Star analyst}_{i,t} \\ & + \sum \beta_{k1} \text{Controls}_{i,j,t} + \sum \beta_{k2} \text{Analyst}_i \\ & + \sum \beta_{k3} \text{Firm} \times \text{Year}_{j,t} + \sum \beta_{k4} \text{Cohort}_{i,t} + \epsilon_{i,j,t} \end{aligned}$$

	(1) BoldD	(2) Bold	(3) Accuracy	(4) MakeFcast	(5) AbsAR
Milestone age	0.027*** (0.010)	0.008*** (0.003)	0.017* (0.009)	0.043** (0.021)	0.402** (0.183)
Milestone age $\times$ Star analyst	-0.051* (0.027)	-0.017** (0.007)	0.035 (0.023)	-0.027 (0.049)	0.051 (0.333)
Observations	52,877	52,877	52,877	19,710	12,463
Adj. R^2	0.094	0.508	0.802	0.124	0.274
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
<i>p</i> -value: $\beta_{\text{Milestone age}} + \beta_{\text{Milestone age} \times \text{Star analyst}} = 0$	0.335	0.151	0.013	0.712	0.106

Table A.6: Milestone Ages and Analyst Forecasting: Alternative Outcome Measures

This table analyzes changes in forecasting behaviors during milestone ages with alternative measures of outcomes. *Bold(rel)* is *Bold* minus the minimum *Bold* for the same firm and same fiscal year across different analysts, and scaled by the difference between maximum and minimum value. *BoldD(60)* and *Bold(60)* are calculated in the same way as *BoldD* and *Bold* but we require the consensus forecast to be within 60 days. *BoldD(ave)*, *Bold(ave)*, and *Accuracy(ave)* are the mean of *BoldD*, *Bold*, and *Accuracy* based on all forecasts issued by an analyst before fiscal year-end and within the one-year horizon. *MakeFcast5* and *MakeFcast7* are similar to *MakeFcast* but with extended response windows of [0, 4] and [0, 6] of an earnings announcement, respectively. *AbsCAR* is the two-day absolute cumulative abnormal returns calculated as the firm's daily stock return adjusted by value-weighted market return on the days [0, 1] when an analyst issued a report, multiplied by 100. The explanatory variable of interest is *Milestone age*. The coefficients on the constant term and the same set of control variables in Table 4 are not presented for brevity. We include analyst, firm-year, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by the analyst and firm-year are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Bold(rel)	Accuracy(rel)	BoldD(60)	Bold(60)	BoldD(ave)	Bold(ave)	Accuracy(ave)	MakeFcast5	MakeFcast7	AbsCAR
Milestone age	0.012** (0.005)	0.001 (0.003)	0.031*** (0.011)	0.005** (0.002)	0.015* (0.008)	0.003 (0.002)	0.020*** (0.008)	0.038** (0.018)	0.040** (0.018)	0.421* (0.235)
Observations	52,873	52,873	41,923	41,923	52,877	52,877	52,877	19,710	19,710	9,463
Adj. R^2	0.307	0.531	0.038	0.419	0.115	0.558	0.844	0.131	0.134	0.296
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7: Milestone Ages and Analyst Forecasting: Extreme Boldness

This table analyzes changes in extreme forecast boldness during milestone ages within the Chinese analyst sample. The dependent variables are *BoldD#*, dummy variables equal to one if an analyst's most recent forecast is more than # standard deviations away from the consensus. The explanatory variable of interest is *Milestone age*. The coefficients on the constant term and the same set of control variables in Table 4 are not presented for brevity. We include analyst, firm-year, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by analyst and firm-year are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

	(1)	(2)	(3)	(4)	(5)
	BoldD1.2	BoldD1.5	BoldD2	BoldD2.5	BoldD3
Milestone age	0.019** (0.009)	0.019** (0.008)	0.017*** (0.006)	0.010* (0.006)	0.005 (0.005)
Observations	52,877	52,877	52,877	52,877	52,877
Adj. R^2	0.088	0.083	0.086	0.092	0.100
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Table A.8: Milestone Ages and Analyst Forecasting: 2011–2019

This table analyzes changes in forecasting behaviors during milestone ages within the Chinese analyst sample from 2011 to 2019. In Columns 1 to 3 we analyze the forecast characteristics *BoldD*, *Bold*, and *Accuracy* for analysts' most recent forecasts before the fiscal year ends. In Column 4 we analyze *MakeFcast* and in Column 5 we analyze *AbsAR*. The explanatory variable of interest is *Milestone age*. The coefficient on the constant term and the same set of control variables in Table 4 are not presented for brevity. We include analyst, firm-year, and age cohort fixed effects. See Table A.1 for detailed variable definitions. Standard errors clustered by the analyst and firm-year are in parentheses. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance.

	(1)	(2)	(3)	(4)	(5)
	BoldD	Bold	Accuracy	MakeFcast	AbsAR
Milestone age	0.031*** (0.011)	0.005* (0.003)	0.019* (0.010)	0.051** (0.022)	0.539*** (0.183)
Observations	42,107	42,107	42,107	16,102	10,131
Adj. R^2	0.093	0.509	0.796	0.129	0.325
Controls	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes
Firm $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes

Table A.9: Placebo Tests Using Ages Ending in Different Digits

This table analyzes changes in professional behaviors at ages ending in different digits as placebo tests. Each coefficient corresponds to a separate estimation (20 estimations in total). The dependent variables in Columns 1 and 2 are *BoldD* and *Job quit*, respectively. The explanatory variable of interest is *X-ending age*, a dummy variable equal to one if an individual enters an age ending in *X*. We include the same control variables and fixed effects as in the main analyses (Tables 2 and 4). Coefficients on the constant and control variables are omitted for brevity. See Table A.1 for detailed variable definitions. Standard errors are clustered by analyst and firm-year in Column 1 and by employee in Column 2. *, **, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively.

$$Professional\ Behavior_{i,t} = \beta_0 + \beta_1 X\text{-ending}\ age_{i,t} + \sum \beta_{k1} Controls_{i,t} + \sum \beta_{k2} FEs + \epsilon_{i,t}$$

	(1) BoldD	(2) Job quit
Milestone age (9-ending age)	0.019** (0.009)	0.0018*** (0.0006)
0-ending age	-0.005 (0.008)	0.0022*** (0.0006)
1-ending age	-0.004 (0.009)	0.0120*** (0.0006)
2-ending age	0.002 (0.009)	-0.0043*** (0.0006)
3-ending age	-0.009 (0.009)	-0.0059*** (0.0006)
4-ending age	-0.007 (0.009)	-0.0032*** (0.0006)
5-ending age	-0.011 (0.009)	-0.0032*** (0.0006)
6-ending age	0.011 (0.009)	-0.0007 (0.0006)
7-ending age	0.014 (0.010)	0.0007 (0.0006)
8-ending age	-0.012 (0.010)	-0.0002 (0.0006)
Observations	52,877	6,003,294
Controls	Y	Y
Individual & Cohort FE	Y	Y
Firm-Year/Country-Year-Role	Y/N	N/Y

Survey Questionnaire

Basics

- Q1. What is your age in years?
- Q2. What sex were you assigned at birth?
- Male
 - Female
 - Prefer not to say
- Q3. This is an attention check to ensure data quality. Please select “Horse” from the list below.
- Dog
 - Cat
 - Elephant
 - Horse
 - Giraffe
 - Lion

If respondents select anything other than “Horse,” the survey ends automatically.

Consideration of Change

- Q4. Are you currently planning, seriously considering, or have you recently made a change in your work or professional life this year? Examples include changing jobs, switching roles, pursuing education or training, or approaching your current work differently.
- Definitely not
 - Probably not
 - Unsure
 - Probably yes
 - Definitely yes

If you answered 4 or 5 to Q4, please continue with the rest of the survey. Otherwise, skip to Question 7.

Type of Change and Reasons

- Q5. If you’ve recently made or are considering a change in your professional life, what does it involve? Please rate how much each of the following applies to your situation, from 1 (Not at all) to 7 (Extremely).
- Switching to a different employer
 - Taking on a new role at your current employer
 - Changing how you approach current work (e.g., mindset, values, tasks, priorities)
 - Pursuing more education or training (part- or full-time)
 - Taking a break or stepping away from the workforce
 - Starting your own business or freelancing
 - Switching to a different field or industry
 - Other (please specify):
- Q6. What are your main reasons for considering or making a change in your professional life? Please rate each reason based on how important it is to you, from 1 (Not at all important) to 7 (Extremely important).
- Desire for greater autonomy in your work (e.g., independence in decision-making)

- Better alignment between your work and your strengths
- Desire to make a greater social impact
- Seeking more meaning and purpose in your work
- Seeking growth through new or more challenging responsibilities
- Promotion or increased compensation
- Desire more flexibility in when and where you work
- Desire for more recognition or status
- Concern about job security or risk of layoff
- Changes in family or life circumstances
- Health issues
- Planning to move or relocate
- Toxic or unsupportive work environment
- Other (please specify):

Value Alignment and Work Satisfaction

Q7. Do you feel your current work reflects your values?

- Not at all
- Slightly
- Somewhat
- Mostly
- Very much so

Q8. How satisfied are you with your current work?

- Not at all satisfied
- Slightly satisfied
- Moderately satisfied
- Very satisfied
- Completely satisfied

Demographics

Q9. What is the highest level of education you have completed?

- Less than high school
- High school diploma or GED
- Some college, no degree
- Associate's degree (AA, AS)
- Bachelor's degree (BA, BS)
- Master's degree (MA, MS, MBA)
- Doctorate or professional degree (PhD, MD, JD, etc.)
- Prefer not to say

Q10. What main industry do you currently work in?

- Education
- Healthcare
- Retail & E-commerce
- Food Services & Hospitality

- Technology
- Administrative
- Finance
- Manufacturing
- Government
- Other (please specify):

Q11. What is your total annual household income before taxes?

- Less than \$25,000
- \$25,000–\$49,999
- \$50,000–\$74,999
- \$75,000–\$99,999
- \$100,000–\$149,999
- \$150,000 or more
- Prefer not to say