The Review of Financial Studies

Human Capital Portability and Careers in Finance

Janet Gao
McDonough School of Business, Georgetown University, United States

Wenyu Wang
Kelley School of Business, Indiana University, United States

Yufeng Wu
Fisher College of Business, the Ohio State University, United States

How does firm-specific human capital shape careers in the finance industry? We build a dynamic model where workers accumulate portable and nonportable (firm-specific) human capital and learn about their match quality with employers. Estimating the model using granular data on M&A advisory bankers, we show that a large fraction of bankers' human capital is nonportable, ranging from 12% to 46% across different firm types. Bankers make a dynamic trade-off between portability and returns on human capital, leading to time-varying job preferences over their life cycle. Our results have broad implications for careers in finance and the provision of financial services. (*JEL* J20, J24, J44, J63, G24, G34)

Received: June 24, 2022; Editorial decision: March 9, 2024
Editor: Gregor Matvos
Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

The financial services industry accounts for over 18% of the U.S. gross domestic product (GDP) and employs over 9 million people as of 2022 (BLS). This industry relies on highly skilled workers to perform complex tasks, such as building relationships with clients, developing expertise regarding a

We thank Gregor Matvos (the editor), two anonymous referees, Tim Johnson, Ron Kaniel, Miguel Palacios, Neil Pearson, Toni Whited, Mindy Xiaolan, and Ben Zhang, as well as all seminar and conference participants at Indiana University, ITAM, PHBS, Tilburg University, University of Illinois, University of Minnesota, University of Rochester, University of Toronto, University of Wisconsin, Columbia junior workshop, Early Career Women in Finance Conference, CICF, EFA, and SFS Cavalcade. Wenyu Wang gratefully acknowledges financial support from the Daniel C. Smith Fellowship. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Yufeng Wu, wu.6251@osu.edu.

The Review of Financial Studies 37 (2024) 2732–2778

https://doi.org/10.1093/rfs/hhae033 Advance Access publication July 15, 2024

specific industry or market segment, and managing teams inside the firm.[1] Given that client industry and teams differ across firms, workers accumulate substantial firm-specific capital in the process. As characterized by the prior literature, firm-specific human capital involves tacit knowledge regarding an organization, familiarity with its procedures, and relationships with coworkers and clients. It is nonportable across firms, and thus is lost during job transitions (Becker 1962; Parsons 1972; Zingales 2000; Lazear 2009; Marx, Strumsky, and Fleming 2009; Berk, Stanton, and Zechner 2010). While it is theoretically straightforward that human capital portability should affect worker choices, there is little evidence on how it shapes worker career dynamics and productivity. In this study, we seek to answer these questions in the setting of the financial services industry.

Empirical research on this topic faces the challenge that human capital portability is an abstract concept and difficult to measure. We overcome this challenge by estimating a dynamic structural model using granular data on the career trajectories and productivity of M&A advisory bankers. Our study examines three questions: What fraction of workers' human capital is firm-specific and thus nonportable? How does portability vary across employers? To what extent does portability shape worker-firm matching and productivity?

We build a dynamic model with heterogeneous employment sectors that endogenizes workers' human capital accumulation and career choices. In this model, workers accumulate both portable and nonportable human capital through deal-advising. Portability is defined as the fraction of human capital that is firm-specific. We find that a significant fraction of human capital is nonportable, and relative to a counterfactual world with perfectly portable human capital, nonportability dampens workers' mobility by 32% and lowers the value of financial services they produce by 5%.

We are also able to quantify the heterogeneity of portability across firms and its effects on worker-firm matching. The M&A advisory industry, like many other financial services industries, consists of two types of firms (sectors): bulge bracket firms, which are large, diversified firms serving a broad client base, and boutique firms, which are small, focused firms offering customized services to a select group of clients. Our estimates suggest that nonportability is 46% in the boutique sector, much higher compared to 12% in the bulge bracket sector. Workers, however, do not overwhelmingly flock to the bulge bracket sector, because they can earn higher returns on their human capital in boutique firms. A life cycle pattern emerges from this trade-off: workers start their careers in the high-portability sector and migrate to the high-return sector as they become more senior and skilled. This is because junior workers value

[1] For example, investment bankers collaborate with one another to advise clients regarding the suitability and terms of M&A deals and negotiate on their behalf. Asset managers gauge clients' preferences and provide tailored investment solutions based on complex analysis and market projections. Financial analysts interact with managers and institutional investors and lead a group of analysts to provide in-depth projections regarding a company.

the potential career opportunities stemming from portable human capital, while senior workers seek to extract more value from the skills they already have.

Our model features three important elements. First, bankers build up human capital by advising deals (i.e., *learning-by-doing*), and their human capital contains both general and firm-specific components. Second, bankers and firms face uncertainty regarding the match quality between them. High match quality means that a banker has a strong synergy with his employer and thus is more productive. Neither the banker nor the firm observes the match quality directly, but they can learn about it over time (i.e., *learn-about-match-quality*). Together, high human capital and good match quality produce more financial services each period (i.e., a large number of deals advised). Third, financial services generate returns to bankers and their employers (i.e., *return on human capital*), and the total dollar value created by a banker-firm pair depends on their deal volume and the return on each deal.

Each period, bankers face the choice of staying with their current employer, moving to a new firm in the same sector, or transitioning to the opposite sector. Job separation between a banker and a firm is determined by comparing the value generated by the current pair to the expected value arising from matching the bankers to alternative employers; the latter depends on the amount of human capital that the banker can bring to his prospective employments. Our model allows the portability of human capital and the return on human capital to differ across sectors. As such, workers' career choices are shaped by the three key elements in the model: a banker is more likely to leave the current employer if he perceives the match quality to be low. Yet, his incentive to switch jobs is counteracted by the potential loss of firm-specific human capital during the transition. When choosing between the two sectors, the banker takes into account the different portability and return on human capital offered by them.

We estimate the model using granular data on the career paths and performance of bankers in the M&A advisory industry. This empirical setting offers several advantages. First, firm-specific human capital is valuable in this industry, as M&A advisory requires bankers to collaborate with team members and build relationships with targeted clients. Second, the two-sector structure of this industry allows us to assess worker-firm matching and workers' career trade-offs across firms. More importantly, the above features of this industry are shared by other skill-intensive occupations in the broad finance industry. Finally, this industry setting allows for a unique data opportunity, where we can track the same banker over time and examine how their productivity changes with experiences and job transitions.

With this data, we identify human capital portability using the changes in banker performance around job transitions. Generally speaking, bankers with more firm-specific human capital should experience a greater performance decline after transitions. Yet, such a performance decline is partially offset by a selection effect: bankers choose to depart because they have been performing poorly. We endogenize the selection effect in the model and isolate the loss of

nonportable human capital in our estimation. Our result suggests that human capital portability is substantially lower for boutique firms than for bulge bracket firms. Of the human capital gained by bankers in bulge bracket firms, 88% is portable. This fraction drops to 54% for bankers in boutique firms. In the meantime, bankers' revealed preference suggests that they view the return on human capital to be 3% higher in boutique firms than in bulge bracket firms, after adjusting for other nonpecuniary factors that are latent to econometricians (e.g., job stability, prestige, and private benefits derived from discretion and autonomy). In all, workers earn higher return on human capital in boutique banks but acquire more generalizable skills in bulge bracket banks.

With these estimates, we evaluate how important human capital portability is for labor mobility, worker-firm matching, and the production of financial services. We also trace these effects over bankers' career stages. Consistent with the prior literature, we first document that firm-specific human capital impedes worker mobility. This effect is more pronounced for boutique bank employees, because bankers accumulate more firm-specific human capital in that sector. Compared to bankers in bulge bracket firms, those working in boutique firms are less likely to leave and are willing to tolerate worse match quality, as evidenced by more severe underperformance before job separation. To quantify the impact of this portability friction on workers' career outcomes, we compare the baseline model prediction with the scenario of perfect portability, where there is no loss of human capital during job transitions. Our results suggest the estimated nonportability in our setting dampens workers' mobility by 32% and lowers the total value of financial services produced by more than 5%. The portability friction is costliest to middle-career bankers. At this stage of their career, many bankers are still searching for better-matched employers, but they have accumulated substantial firm-specific human capital, making it costly to pursue good outside options. This result highlights that firm-specific human capital could aggravate other labor market frictions.

We also show that bankers' sectoral preferences change over their career stages (i.e., the life cycle effect). Novice bankers prefer bulge bracket banks because they value generalizable skills and hope to retain the flexibility to relocate to other firms in the future. As bankers become more seasoned, they increasingly migrate to boutique banks to pursue higher returns on their human capital. Our model predicts that a 1-year increase in a banker's experience is associated with an approximately one-percentage-point higher likelihood of the banker being in the boutique sector, which matches the pattern observed in the data. This finding suggests that bulge bracket firms act as "incubators" of human capital, where employees can acquire general knowledge and skills that prove to be valuable for their future careers.

Why do bankers lose so much human capital when they move to another firm and continue in the same line of work? We investigate two potential sources of firm-specific human capital. The first source is the industry expertise of a firm.

This is motivated by the fact that industry expertise is a source of competitive differentiation across M&A advisors. As bankers accumulate deal-making experiences in a firm, they accumulate industry-specific knowledge, such as the knowledge regarding regulatory landscape, technological advancement, and product market dynamics. Such knowledge may continue to apply if they move to a new firm covering the same industry, but not if the new firm covers a completely different set of industries. To explore this potential channel, we extend our framework by modeling bankers' human capital portability as a function of the compatibility score between their current and next employers. The score captures the degree of overlap in the two firms' industry coverage, and the extent to which bankers can apply their industry expertise in their next employments. We show that high compatibility is associated with a smaller reduction in productivity during job transitions, and for an interquartile increase in the compatibility measure, our estimated human capital nonportability parameter declines by 17.8 percentage points.

The second source of firm-specific human capital we consider is teamwork. Teamwork is a common way of organizing complex work in the modern economy (Lazear and Shaw 2007). In teams, coworkers learn from each other and develop complementary skills (e.g., Bartel et al. 2014; Herkenhoff et al. 2018). The dissolution of teams can thus lead to severe loss of productivity (Baghai, Silva, and Ye 2019). We extend the model to incorporate the heterogeneity across bankers in terms of within-firm collaboration intensity. Estimation based on the extended model suggests that an interquartile increase in collaboration intensity is associated with an 18.8-percentage-point increase in human capital nonportability.

These results suggest that industry expertise and teamwork contribute to the nonportability of worker human capital in the finance industry. In the data, boutique firms have a narrower industry coverage compared with their bulge bracket peers, and bankers in boutique banks on average collaborate more intensively with their colleagues, both of which contribute to lower human capital portability. Quantitatively, these factors account for substantial variation in the portability gap across the bulge bracket and the boutique sectors.

In closing, we discuss some of our modeling choices. First, our model abstracts from discussing wages or compensation contracts by assuming frictionless bargaining. Under this assumption, a banker splits the surplus with his employer such that the banker is compensated on par with his outside option at any time, plus a share of the surplus. They remain matched as long as doing so generates a higher joint surplus relative to their respective outside options. We discuss the plausibility of these assumptions in Section 5, where we show that our setting is consistent with the sequential bargaining framework in the literature (e.g., Cahuc, Postel-Vinay, and Robin 2006; Jarosch 2023). Second, we do not impose intrinsic talent heterogeneity across workers in the model, but instead focus on experience-based human capital. This is because we are interested in the accumulation and loss of human capital for a given worker,

and identify firm-specific human capital through the change in productivity of the same worker. Most of our analyses are performed at the worker level across various career stages, which makes such experience-based human capital more relevant. Moreover, because of our micro-level focus on individual workers' career dynamics, we treat the human capital portability in each sector as fixed. We do not speak to long-run dynamics, as industry structure and production function could change, potentially because of regulatory and technological factors. Finally, we show that our inferences remain robust as we consider other labor market frictions, such as exit, promotion, and noncompete clauses, as well as the influence of the Global Financial Crisis. They are also robust if we allow the two sectors to have different investment opportunities.

This study contributes to several strands of literature. To start, we are related to the burgeoning literature on careers in the financial industry see (see Ellul, Pagano, and Scognamiglio 2021, for a summary of the literature). We are the first to quantify the portability of workers' human capital in the financial industry, and to document how portability shapes worker career paths. While our model is estimated using data from the M&A advisory industry, our findings can be generalized to other segments of the financial industry, because they share several key elements of our model. First, in many financial service jobs, workers tend to accumulate a significant amount of firm-specific human capital for reasons such as clientele specialization, market focus, corporate strategy, and teamwork. The accumulation of firm-specific human capital leads to productivity losses upon job switches. Our estimates regarding the productivity loss upon job switches are of value to understanding job switches in other sectors of the financial industry. Second, other financial service sectors, such as asset management, also feature a polarized industry structure, with a few large firms accounting for a significant fraction of the market share and many small firms making up for the rest of the market. For example, in the mutual fund industry, the top-five fund families occupy over 60% of the market share; in the hedge fund industry, funds with above $5 billion AUMs account for over 70% of the market share.[2] Finally, the trade-off between scale and returns is observed in many financial sectors, especially in actively managed funds (e.g., Chen et al. 2004; Pástor, Stambaugh, and Taylor 2015; Zhu 2018; Pastor et al. 2021). Thus, our findings regarding workers' career transitions between large and small firms are relevant for these segments of the financial services industry, which broadly share these features.

We are also related to the recent literature analyzing the matching between workers and firms in the finance industry. Prior studies have documented that poor-performing asset managers, bankers who incurred default in their portfolios, and advisors with misconducts subsequently move to smaller, less prestigious, and high-misconduct institutions (Ellul, Pagano, and

[2] See Travillian (2022) regarding evidence of the mutual fund industry. Mackenzie (2023) discusses the concentration of the hedge fund industry.

Scognamiglio 2020; Gao, Kleiner, and Pacelli 2020; Egan, Matvos, and Seru 2019). Consistently, our results suggest that high-performing bankers migrate to the sector that offers higher returns to human capital. In this regard, our results are consistent with Deuskar et al. (2011), who find that high-performing mutual fund managers can enter side-by-side arrangements with hedge funds to achieve higher returns to human capital.[3]

Second, we add to the research on firm-specific human capital. A long-standing literature predicts that firm-specific skills play an important role in determining labor market outcomes and corporate policies (see, e.g., Becker 1962; Jacobson, LaLonde, and Sullivan 1993; Jaggia and Thakor 1994; Acemoglu and Pischke 1999; Wasmer 2006; Huckman and Pisano 2006; Groysberg, Lee, and Nanda 2008; Gathmann and Schönberg 2010). Our paper contributes to this discussion by *quantifying* the extent to which human capital is nonportable, combining structural estimation and granular data on M&A advisors' deal-making histories. While some existing studies focus on the role of industry- and occupation-specific skills (Lee and Wolpin 2006; Gathmann and Schönberg 2010), our result suggests that workers in skill-intensive industries still possess substantial nonportable human capital, even if they belong to the same occupation and perform similar tasks. Importantly, we assess the extent to which the portability friction influences workers' career.

Third, our study contributes to the literature on capital (mis)allocation. Classic q-theory suggests that capital should flow to the most efficient users to achieve the highest productivity (Jovanovic and Rousseau 2002). Existing studies mainly focus on physical capital allocation and examine how various frictions distort the flow of capital (Maksimovic and Phillips 2001; Yang 2008; Warusawitharana 2008; Eberly and Wang 2009; Lanteri 2018; Li and Whited 2015). We relate to this literature by studying the allocation of human capital. We document that the lack of portability in firm-specific knowledge represents a key friction that distorts human capital allocation. In this regard, our paper is closely related to Sun and Xiaolan (2019), who show that intangible capital embodied in firms' employees significantly influences how firms finance intangible investments and their capital structures. Our study complements Sun and Xiaolan (2019) by focusing on workers' employment choices. We also use micro-level data to measure the extent to which the nonportability of human capital influences productivity and the structure of the M&A advisory industry.

Methodologically, our paper belongs to the growing literature that employs structural model calibration or estimation to answer important questions in the M&A market (see, e.g., Yang 2008; Albuquerque and Schroth 2010, 2015; Gorbenko and Malenko 2014; Levine 2017). Our paper contributes to this

[3] At the same time, our setting differs from the one in Deuskar et al. (2011) in important ways. In Deuskar et al. (2011), successful managers can enter side-by-side arrangements with hedge funds, and thus appear "retained" by mutual funds. However, M&A bankers generally do not have the option to enter such arrangements with other banks. Bankers seeking higher returns to human capital have to switch jobs.

literature by focusing on a different angle—the career decisions of M&A advisors, who are key intermediaries in facilitating deal-making in the M&A market. We quantify how frictions in advisors' human capital development influence the composition of the industry.

1. Model

1.1 Model setup

We model a continuum of investment bankers, who hold positions within investment banks (i.e., firms) to perform M&A advisory services (that is, to produce). There are two types of advisory banks in the economy: bulge bracket banks and boutique banks. Thus, our model embeds important heterogeneity across firms in terms of organizational structure and worker characteristics. A key objective of the model is to characterize individual bankers' career choices and to examine the labor (re)allocation across sectors.

Each job is modeled as a pair consisting of an investment banker i and a bank b. As in previous studies (see, e.g., Jovanovic 1979; Nagypál 2007), our model features a pair-specific match quality, $\mu_{i,b}$. Match quality reflects the synergy between a banker and a bank. A banker should be more productive when he "fits in" with the bank's organization, benefits from interactions with his colleagues, and thrives under the bank's culture. We assume that $\mu_{i,b}$ is drawn when a pair is formed and that it remains unchanged until the pair breaks up. As the individual switches to a new employer b', a new match quality is drawn. The match quality is i.i.d. across pairs, with $\mu=1$ denoting a high-quality match and $\mu=0$ denoting otherwise. μ follows a common Bernoulli distribution:

$$P\{\mu=1\}=1-P\{\mu=0\}=q. \tag{1}$$

The distribution is common knowledge, but the realization of $\mu_{i,b}$ is *unobservable* to any agent in the model.

Human capital is a key element in our model. Investment bankers use their human capital to advise M&A deals and generate profits for their employers. Meanwhile, they also accumulate human capital through their deal-advising experience (i.e., learning-by-doing, as in Parsons 1972 and Nagypál 2007). We characterize two types of human capital—portable and nonportable. Portable human capital captures a banker's generalizable skills, such as codified, analytical skills, familiarity with the general procedures, and laws and institutional knowledge. Portable human capital can be carried over with the banker to a new employer following a job switch. Nonportable human capital is employer-specific, including relationships with colleagues and clients of a banker's current employer, and the ability to work with the organizational structure and tap into the resources. Nonportable human capital evaporates once the banker switches employers (see, e.g., Topel 1991). We denote portable human capital as h and nonportable human capital as ω.

Labor is the only input to production. We measure the production output of each banker-firm pair based on the number of deals advised. In each period t,

banker i who works for bank b advises $n_{i,b,t}$ deals. The deal number $n_{i,b,t}$ is stochastic and follows a Poisson distribution:[4]

$$P\{n_{i,b,t}=N\}=\frac{\left(m_{i,b,t}\right)^{N}}{N!}e^{-m_{i,b,t}}, \tag{2}$$

where N is the realized deal number and $m_{i,b,t}$ is the parameter that controls the deal arrival rate. We let $m_{i,b,t}$ depend on the match quality and the banker's human capital:

$$m_{i,b,t}=\left(a\cdot\mu_{i,b}+c\right)\cdot\left(h_{i,t}+\omega_{i,t}\right)+b. \tag{3}$$

Equations (2) and (3) imply that a banker's output in a given period is determined by three factors: the match quality between the banker and his employer, the amount of portable and nonportable human capital that he has accumulated, and some randomness as captured by the Poisson process. The coefficients a, b, and c are model parameters to be estimated.

We use π to denote the profits from deal advising:

$$\pi_{i,b,t}=\lambda_s\cdot n_{i,b,t}, \tag{4}$$

where s denotes the sector, with $s=0$ indicating bulge bracket banks and $s=1$ indicating boutique banks; λ_s is the sector-specific parameter that controls the return per deal offered by banks in this sector. When λ_s is large, the M&A advisor creates greater profit from each deal and thus generates a higher return to human capital supplied by the banker. The profit is then split between the investment banker and the advisory firm. Anecdotal evidence suggests that boutique firms incur lower overhead costs and distribute more revenue to bankers, and are thus likely to be more efficient than bulge bracket banks. Yet, we do not impose any prior on the relative magnitude of λ across sectors, but instead let this parameter be determined by the data. Finally, we note that, in the estimation process, λ_s will be identified through the bankers' revealed preference (i.e., their choices between the two sectors), and thus λ_s incorporates the effects of many latent factors that influence the returns to human capital perceived by bankers. For example, if bankers are generally risk averse and dislike the more volatile cash flows from less established firms (boutiques), λ adjusts downward to reflect such a preference.

In addition to generating profits, advising deals also builds a banker's human capital (i.e., learning-by-doing). In the absence of a job switch, a banker's

[4] In the model, we assume deals are homogeneous and thus the deal number is a sufficient statics of output. In the data, however, deals differ in their size and complexity. A bigger and more complex deal would require more time and effort from investment bankers; it also offers more valuable learning opportunities for the participating bankers and allows them to charge higher fees. To account for such heterogeneity, we rely on volume-adjusted deal numbers, as opposed to simple deal counts, as our empirical measure. Internet Appendix C provides more details on constructing this measure. A Poisson process can also effectively model nonintegral outcomes (Silva and Tenreyro 2011; Cohn, Liu, and Wardlaw 2022), such as the adjusted deal numbers in our setting.

human capital evolves following the law of motion:

$$\omega_{i,t+1} = \rho \cdot \omega_{i,t} + \delta_s \cdot \ell(h_{i,t} + \omega_{i,t}) \cdot n_{i,b,t}, \tag{5}$$

$$h_{i,t+1} = \rho \cdot h_{i,t} + (1 - \delta_s) \cdot \ell(h_{i,t} + \omega_{i,t}) \cdot n_{i,b,t}, \tag{6}$$

where $1-\rho$ controls the fraction of old human capital that becomes obsolete and $\ell(x)$ determines the speed of learning-by-doing. If $\ell(x)$ is a positive constant, then human capital builds at a constant rate. If $\ell(x)$ is positive but decreasing in x, then human capital accumulation slows down as the level of human capital goes up, which is a common feature of many learning models. This feature captures the idea "the low-hanging fruit gets picked first." The parameter $\delta_s \in [0, 1]$ indicates the proportion of human capital acquired through each deal that is firm-specific: when δ_s is high, a larger fraction of human capital accumulates in its nonportable component. We allow δ_s to vary across sectors, so bankers accumulate different portions of portable human capital when they work in bulge bracket banks versus boutique banks.

Overall, there are two key parameters differentiating the bulge bracket and boutique sectors: the return on human capital (λ_s) and the portability of human capital ($1-\delta_s$). Such cross-sectoral differences suggest that bankers working for boutique firms may accumulate firm-specific human capital at a different speed from bankers in bulge bracket firms. Boutique and bulge bracket firms may also utilize bankers' human capital differently, thus generating differential profits from every unit of human capital. We allow the two parameters to vary across the two sectors, thus permitting a meaningful return-portability trade-off when bankers choose which sector to join.

The last key element of our model is the perceived match quality. Although true match quality is unobservable, agents can form their beliefs by extracting information from the realized deal volume, $n_{i,b,t}$. As Equation (2) suggests, $n_{i,b,t}$ serves as a signal of the deal arrival rate, $m_{i,b,t}$, which is, in turn, a function of the match quality $\mu_{i,b}$. At the beginning of each period t, the banker perceives that his match quality with the current employer is high with a probability of $p_{i,b,t}$. After observing the current period deal volume, $n_{i,b,t}$, he updates his perception to $p_{i,b,t+1}$ following the Bayes' Rule:

$$\begin{aligned} p_{i,b,t+1} &= P\{\mu_{i,b} = 1 | n_{i,b,t} = N, p_{i,b,t}\} \\ &= \frac{p_{i,b,t} \cdot \frac{(m_1)^N}{N!} e^{-m_1}}{p_{i,b,t} \cdot \frac{(m_1)^N}{N!} e^{-m_1} + \left(1 - p_{i,b,t}\right) \cdot \frac{(m_0)^N}{N!} e^{-m_0}}, \end{aligned} \tag{7}$$

where m_1 and m_0 are the Poisson arrival rates in Equation (3) when $\mu_{i,b} = 1$ and $\mu_{i,b} = 0$, respectively. This belief-updating process suggests that a banker considers his employer more likely to be a good match if he has experienced a higher deal volume.

1.2 Bellman equations

Each banker-bank pair in our model is characterized by a vector of state variables, (s,h,ω,p), which corresponds to the bank sector, the general and specific human capital the banker possesses, and the perceived match quality of the pair. The model timeline, shown in Figure 1, flows as follows: at the beginning of each period, a banker chooses between staying with the current employer and switching to a new bank before production takes place. Although the career choice is made at the beginning of the period, we assume that the relocating banker joins the new employer at the end of the period.[5] Upon switching employment, the perceived match quality of the new banker-bank pair follows a common prior: $P\{\mu=1\}=q$. Lastly, at the end of each period, there is an exogenous probability η that the banker exits the industry and loses all his continuation value.

We use variables with a prime to represent the values at the beginning of the next period, and the Bellman equation below characterizes the value function for an employment pair consisting of an investment banker and his current employer:

$$U(s,h,\omega,p)=\max_{d=\{0,1,2\}}\pi+\beta\cdot(1-\eta)\cdot E\left[U(s,h',\omega',p')\right]$$
$$+\beta\cdot(1-\eta)\cdot\{\chi\,\Sigma_1(s,h,\omega,p)\cdot\mathbf{1}_{d=1}+\chi\,\Sigma_2(s,h,\omega,p)\cdot\mathbf{1}_{d=2}\}, \tag{8}$$

where $d=\{0,1,2\}$ represents the decision of staying with the current employer, switching to a new firm within the same sector, or switching to a new firm in the opposite sector, respectively, and the benefits associated with switching

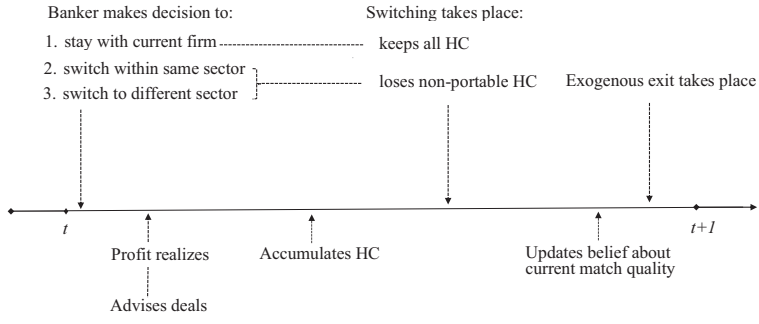

Figure 1
Model timeline

[5] This assumption is consistent with the fact that many bankers switch jobs after they receive their year-end bonuses from their current employers even if they had decided to leave earlier in the year.

employment equal:

$$\Sigma_1(s,h,\omega,p)=E\left[U(s,h',0,q)\right]-E\left[U(s,h',\omega',p')\right], \tag{9}$$

$$\Sigma_2(s,h,\omega,p)=E\left[U(1-s,h',0,q)\right]-E\left[U(s,h',\omega',p')\right]. \tag{10}$$

The first term on the right-hand-side of Equation (8) is the flow profit generated in the current period as shown in Equation (4), which is shared by the banker and the bank. The second term is the continuation value if the banker stays with the current employer, and the third term is the surplus the banker expects to gain if he switches to a new employer within or across the sector. Equation (9) captures the expected surplus from switching to a new bank in the current sector (in which case s remains the same), and Equation (10) describes the expected surplus from switching to a new bank in the opposite sector (in which case s becomes $1-s$ in the next period). The banker gets a fraction of χ of the total surplus when he is paired with a new employer. We assume it is costless to create or destroy positions within a bank, so the value of a job vacancy equals zero. Upon job transition, only portable human capital, h, is carried over to the new employer, and nonportable human capital, ω, is lost. The banker's perceived match quality with the new employer resets to the common prior q at the beginning of his new employment.

The Bellman equation (8) characterize the value of an employment pair (i.e., a banker and his current employer). This setting follows that of Nagypál (2007) and Jarosch (2023), and the separating decisions are bilaterally efficient (see also Mortensen 1982; Diamond 1982; Moscarini 2005). Specifically, the current employment pair breaks down only if the total surplus of the banker and new employer is higher than that of the current employment pair. Bilateral efficient separations also imply that there is no difference between a banker's voluntary departure and mandatory layoff, because the banker and the bank always agree on the separation decisions in the model.[6] We discuss alternative specifications of separation decisions in Section 5.

1.3 Stationary equilibrium

We denote the cross-sectional distribution of heterogeneous bankers as $f(s,h,\omega,p)$. In the model, $f(s,h,\omega,p)$ evolves over time, driven by four forces: first, the stochastic arrival of M&A deals and bankers' learning-by-doing change bankers' portable and nonportable human capital, h and ω. Second, if bankers stay with their current employers, they update the expected match quality, p, based on the recent deals they advise, and if they switch to a new employer, they reset the perceived match quality to the conditional mean,

[6] Having bilateral efficient separation does not uniquely pin down the value split between the banker and his employer and thus is silent on the banker's compensation. Banker-level compensation data are also lacking. For these reasons, our estimation targets bankers' career transitions and deal advising outcomes, but not their wages.

q. Third, cross-sector job transitions change the labor share of each sector s. Fourth, incumbent bankers exit with an exogenous rate of η each period, and the existing bankers are replaced by an equal number of new entrants into the model economy.

We assume that each entrant enters with zero portable and nonportable human capital, $h=\omega=0$. He meets with a prospective employer in each sector s and observes noisy signals, ζ_s, regarding his match quality with the employer. We specify ζ_s as a random draw from the normal distribution with the mean being the true match quality μ_s (as described in Equation 1) and the standard deviation being σ_ζ. That is, $\zeta_s \sim N(\mu_s, \sigma_\zeta)$. The entrant therefore has an initial perceived probability of a good match, $p_{0,s}$, for the employer he meets in sector s:

$$p_{0,s} = \frac{\psi(\zeta_s; 1, \sigma_\zeta)}{\psi(\zeta_s; 1, \sigma_\zeta) + \psi(\zeta_s; 0, \sigma_\zeta)}, \tag{11}$$

where $\psi(\cdot; \mu, \sigma)$ is the PDF of the normal distribution with a mean of μ and a standard deviation of σ.

The entrant then chooses one prospective employer to join by comparing the value functions in Equation (8) for $s=0$ and $s=1$. This determines the initial sector s he works in. The entrant's state variable, therefore, is $(s, 0, 0, p_{0,s})$.

We define the stationary model equilibrium as follows:

1. In absence of a job switch, h' and ω' follow the law of motion in Equations (5) and (6); upon a job switch, h' is retained while ω' is reset to zero;
2. In absence of a job switch, p' follows the law of motion in Equation (7); upon a job switch, p' is reset to unconditional mean for the employment pair;
3. In the absence of a job switch or upon a job switch within the same sector, s remains unchanged; upon a job switch across sectors, s' is set to $1-s$;
4. The optimal job switch decision is solved by maximizing Equation (8) for both the incumbent firm-banker pairs and the entrant bankers.
5. Let $\Gamma(\cdot)$ denote the transition function governing the cross-sectional distribution of firm-bankers:

   $$f(s', h', \omega', p') = \Gamma(f(s, h, \omega, p)).$$

   $\Gamma(\cdot)$ is consistent with the evolution of firm-banker states and the optimal job switching decisions described above.
6. $f(s, h, \omega, p)$ remains stationary:

   $$f(s', h', \omega', p') = f(s, h, \omega, p).$$

It is important to note that in a stationary equilibrium, there may exist a net labor flow from one sector to another. The labor share lost by the sector

"exporting" its workforce is balanced by a greater proportion of new entrants opting to start their careers within that sector. Consequently, the overall labor shares remain constant.

1.4 Model solution

As discussed in Section 1.1, the two sectors (bulge bracket and boutique) differ along two dimensions: the return on human capital (λ_s) and the portability of human capital ($1-\delta_s$). Bankers value the two dimensions differently at different stages of their careers, and this trade-off determines the banker-sector sorting. To illustrate the intuition, we first present and solve a simplified model in Internet Appendix A. With additional assumptions, we can characterize bankers' human capital accumulation and employment value in close-form, which we then analyze to demonstrate the main trade-off when the bankers make their job switching decisions.

To illustrate the trade-off in the full model, we start by specifying the function $\ell(\cdot)$ in Equations (5) and (6) as

$$\ell(x)=\ell e^{-\alpha x}. \tag{12}$$

If $\alpha > 0$, it features a declining learning speed with the growth of human capital, a standard assumption maintained in many learning models. The specification also nests the case of constant learning speed, that is, $\alpha=0$, which we adopt in Internet Appendix A. We estimate the value of α by matching the curvature of bankers' deal volumes over their career paths.

We solve the Bellman equation and the associated bankers' optimal career choice using value function iteration. Based on the model solution, we simulate a panel of bankers and illustrate how their mobility varies with their human capital, the perceived match quality, and the current sector in which they work. Mobility is defined as the probability that an individual banker makes a job switch in a year. Figure 2 displays the results, with panel A (B) showing the results for bankers who are currently employed in the bulge bracket (boutique) sector. Both panels correspond to three-dimensional heat maps with the perceived match quality, p, on the x-axis and the total human capital, $H=h+\omega$, on the y-axis.[7] Labor mobility is shown by the color scale, with lighter colors indicating higher mobility.

Both panels of Figure 2 suggest that the job separation rate decreases with perceived match quality. This is because lower match quality depresses the value of maintaining the existing match and makes a job switch relatively more attractive. For bankers in the boutique sector, they follow a threshold strategy, switching jobs as soon as the perceived match quality drops below a cutoff. The cutoff value depends critically on their human capital. Our estimates in

[7] For this figure, we focus on bankers who have not previously switched jobs in the simulation, so that their portable human capital h, and nonportable human capital, ω, have been accumulating at the same speed.

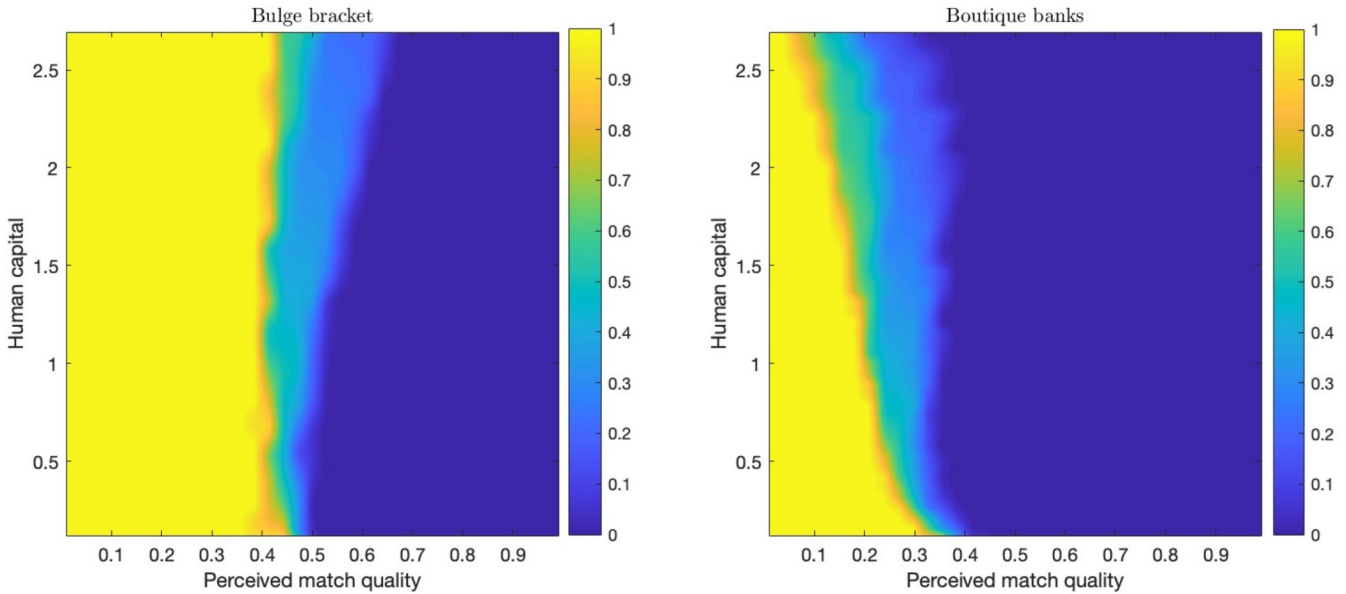

Figure 2
Labor mobility: The effects of human capital and match quality
This figure illustrates the mobility of individual bankers with different levels of human capital and perceived match quality using heat maps. Labor mobility is measured as the probability that an individual banker makes a job switch in a year. Panel A shows the results for the bulge bracket sector, and panel B shows the results for the boutique sector. The x-axis represents the perceived match quality p, and the y-axis represents total human capital, $H = h + \omega$. Lighter colors represent higher probabilities of job switches. The results are based on an average of 10,000 simulations using parameter values reported in Table 4.

Section 2 suggest a large fraction of human capital accumulated within the boutique sector is nonportable and will be lost during job transitions. Thus, the bankers with high human capital find it particularly costly to move, and are willing to tolerate lower match quality to avoid costly job transitions.

The situation is very different for bankers in the bulge bracket sector, for several reasons. First, as shown in Section 2, bulge bracket bankers' human capital is highly portable, making it easier for bankers to seek new jobs when they perceive a decline in the match quality with the current employer. This increases their mobility rates. Second, as bulge bracket bankers gain experience, they accumulate more human capital and can benefit more from switching to the boutique sector, which offers higher returns on their human capital. This incentive becomes more pronounced for those who have accumulated significant levels of human capital, leading to a more nuanced relationship between mobility and human capital that is different from the patterns observed in the boutique sector.

Next, we analyze the value of human capital portability. We measure the marginal value of portable and nonportable human capital as $\frac{dU}{dh}$ and $\frac{dU}{d\omega}$, with U being the value function defined in Equation (8). Since nonportable human capital cannot be carried over to a new employer, we expect it to be less valuable than portable human capital, that is, $\frac{dU}{d\omega} \leq \frac{dU}{dh}$. We define "portability premium" as the value of portable human capital relative to the value of nonportable human capital:

$$\gamma = \frac{\frac{dU}{dh} - \frac{dU}{d\omega}}{\frac{dU}{dh}}, \tag{13}$$

Figure 3 illustrates how the portability premium varies with match quality and bankers' human capital in the two sectors. Intuitively, the portability premium exhibits a pattern similar to that of bankers' mobility. In the extreme case, where bankers never expect to leave their current employers, there is no distinction between portable and nonportable human capital, and hence, the portability premium equals zero. By the same logic, holding match quality and human capital levels fixed, bankers in bulge bracket firms attach higher value to general human capital while boutique bankers derive greater value from firm-specific human capital. This is because the latter change jobs less frequently, resulting in them assigning more similar values to each unit of portable and nonportable human capital.

Lastly, we examine bankers' sectoral choices, which answer the question of "who works for whom." We simulate from the estimated model a panel of bankers who start their careers in bulge bracket banks and track the fraction of these bankers who move to boutique banks over time. Figure 4 shows that, in the early-career stage, the majority of bankers choose to stay in bulge bracket banks. Among those who start their career in bulge bracket firms, only about 15% switch to the boutique sector in the first 10 years of their career. This ratio climbs rapidly to 23% during the second 10-year period and nearly

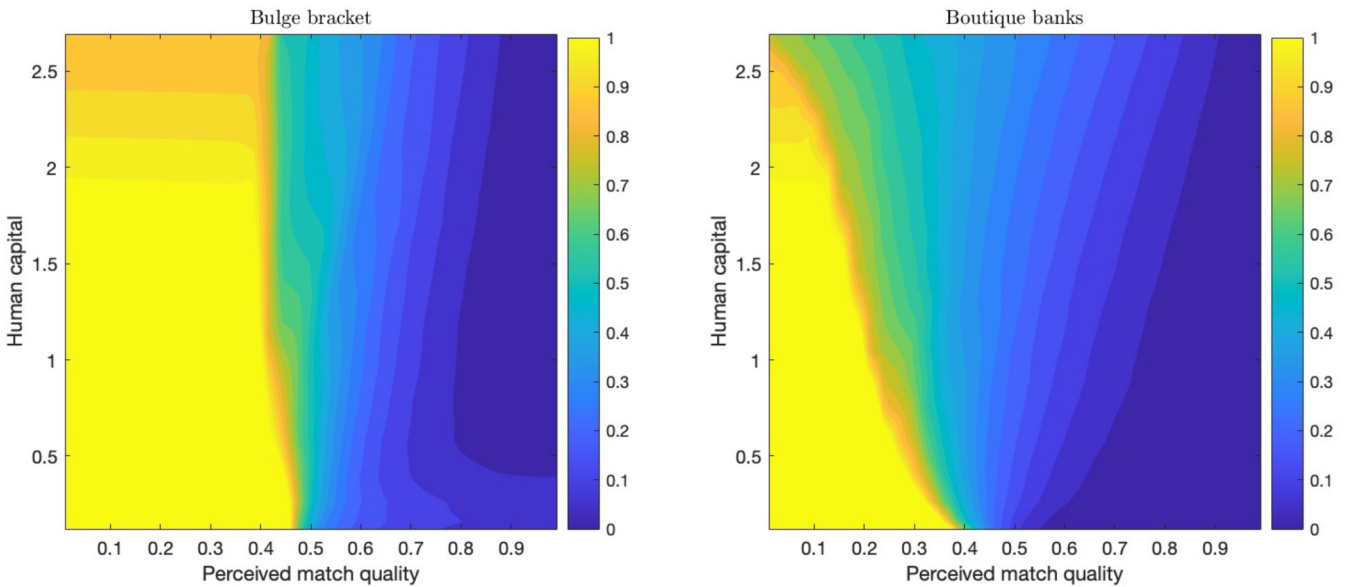

Figure 3
Portability premium
This figure shows how bankers value portable over nonportable human capital. We plot the relation between perceived match quality, existing human capital, and the portability premium using heat maps. The portability premium is defined as the percentage difference between the marginal value of portable human capital and the marginal value of nonportable human capital, as in Equation (13). The left panel shows the results for the bulge bracket sector, and the right panel shows the results for the boutique sector. In both panels, the x-axis indicates perceived match quality p, and the y-axis indicates total human capital, $H = h + \omega$. Lighter colors represent higher levels of portability premium. The results are based on an average of 10,000 simulations using parameter values reported in Table 4.

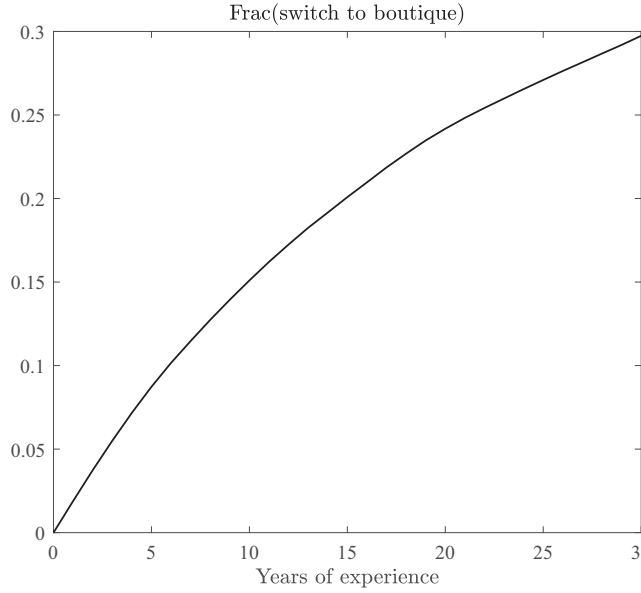

Figure 4
Sector choices: Who works for whom?
In this figure, we graph the relationship between the share of bankers switching to the boutique sector and their work experience (in years). We simulate a panel of bankers who start their careers in bulge bracket firms and track the fraction of these bankers who switch to boutique firms over their career paths. The *x*-axis represents the number of years bankers have worked in the industry, and the *y*-axis represents the fraction of bankers who have switched to boutique firms.

30% after three decades. These results reflect bankers' trade-off between the return and portability of human capital when making sector choices. Moreover, such trade-off varies with bankers' life cycle. Senior bankers have a stronger preference for boutique banks because they possess greater human capital, and the return on human capital plays a dominant role in affecting their career choices. Senior bankers are also more likely to have formed a good match with the current employer from learning and separating from previous employers of bad matches over time. Hence, they are less in need of future job switches, which reinforces their preference for return over portability.

The above analyses illustrate the model's equilibrium predictions with the estimated parameters (shown in Table 4). In Internet Appendix B, we further investigate how the model-implied mobility, portability premium, and the net labor flow between the two sectors vary with different parameter values of δ and λ. Our key takeaway regarding the portability-return trade-off remains similar.

1.5 Model discussion

Like most economic models, our model makes a few simplifying assumptions and leaves out factors that were studied in previous works. In this section, we discuss their impact on our model setup and predictions.

First, we do not impose heterogeneity in worker-intrinsic talent in our model, but instead focus on experience-based human capital (i.e., knowledge and skills acquired through work experience) as the key driver of worker heterogeneity in our model. Our focus is motivated by several reasons. First, the key skills required in M&A deal advising include substantial personal interactions and networking. These abilities can be improved through experience. Consistent with this argument, we confirm a strong correlation between productivity and years of experience in the data. Second, bankers in our sample are highly skilled, carrying job titles of Vice President, Senior Vice President, and Managing Director. They have passed the initial screening of the M&A advisory industry and have demonstrated sufficient ability to lead an investment banking team and advise deals independently. Talent heterogeneity, therefore, is further narrowed in this selected group. Third and perhaps more importantly, we are interested in understanding bankers' career paths, holding fixed their intrinsic attributes. In particular, we study how a banker accumulates human capital over time and how he matches to different types of firms depending on the career stage. Our estimation relies primarily on within-person comparisons, fixing a banker and tracking the changes in his performance over time. For example, our identification of human capital portability arises from the changes in the same banker's productivity around his job transition. Because of these considerations, we believe that the key variation among our sample bankers arises from experienced-based human capital rather than "born" talent.

Second, we do not adopt a two-sided matching model (Akkus, Cookson, and Hortaçsu 2016, 2021). This is because in our framework, bankers make career trade-offs between two sectors (bulge vs. boutique) and not individual firms. In this context, capacity constraint becomes less relevant. Nevertheless, our model also generates a sorting between heterogenous bankers and sectors: bankers with higher expected mobility optimally match with banks that offer higher portability, while bankers with higher human capital optimally match with banks that generate greater returns to labor input.

Third, we assume that bankers acquire human capital through work experience (learning-by-doing), but abstract from the on-the-job training considered in the canonical labor literature (Becker 1962; Acemoglu and Pischke 1998; Almeida and Carneiro 2009). There are typically two types of training in M&A advisory firms: (1) the training sessions offered to entry-level bankers regarding codified knowledge and generalizable skills, and (2) the mentorship by senior bankers and industry experts. We believe the second type of training is more relevant given that our study focuses on skilled bankers who already possess good education background in Business and Economics.[8]

[8] As discussed by Morrison and Wilhelm (2007): "Investment bankers rely less upon qualifications acquired in school than they do upon those acquired on-the-job……"; "The skills needed to fulfill this role [investment banking] are hard to pass on at arm's length: they are best learned through day-to-day contact with an expert mentor and once learned, they cannot easily be codified and widely disseminated at arm's length. This type of skill was characterized by Polanyi (1966) as tacit."

In most cases, mentorship is carried out through practice: senior bankers guide junior bankers through deal-making instead of textbooks. This type of training is consistent with the "learning-by-doing" process.

Fourth, human capital portability is assumed to be exogenous in the model. This consideration is driven by the scope of our study as well as the nature of firm-specific human capital in our setting. The goal of our study is not to explore firms' endogenous decision of human capital portability, but to quantify how human capital portability affects worker career outcomes. For individual workers, firms' portability can be viewed as exogenous. In addition, though firms may have the incentive to endogenously alter portability in order to retain skilled workers, such choices are likely constrained by many other factors, including banks' organizational structure and business scope. As discussed in Section 4.1, a bank's industry coverage and expertise give rise to firm-specific human capital. These characteristics are formed over a longer history, driven by various reasons, such as regulatory environment, market conditions, and the founders' expertise, and can be difficult to change in the short term. In addition, the advisory industry has developed over decades into the bi-sector structure, with bulge bracket and boutique firms maintaining drastically different organizational structures. While higher portability may seem attractive to boutique firms, changing it could require a firm to go through significant expansion in scope, which could be overall value-destroying to the bank.

2. Estimation

In this section, we describe how we estimate the model parameters, including the sample construction, the simulated method of moments (SMM) estimator, and the intuition behind the estimation process.

2.1 Data and sample construction

We collect the identities and deal-making histories of investment bankers from the MergerMarket database during the period of 2000 through 2018. MergerMarket records M&A deals worldwide with transaction values over $5 million, in which an acquirer purchases at least 30% of the equity stake of a target firm. For each deal, MergerMarket provides detailed information on various deal characteristics, including the identities of the acquirer, the target, the advisory bank, the announcement and completion dates of the deal, and the transaction value. The distinguishing feature of the database is that it provides the names of the investment bankers leading the deals and their employment affiliations. These bankers represent the lead advisors from each advisory firm, and do not include lower-level personnel. This information allows us to track bankers' experience, performance, and their human capital accumulation.

We compile the complete career path of each banker in the sample using information from the BrokerCheck Report, assembled by the Financial

Industry Regulatory Authority (FINRA). FINRA is a regulatory agency that tracks all individuals involved in security dealing and requires those individuals to report their job affiliations at every point in time. This database allows us to pin down the precise timing of bankers' job transitions.

We classify an M&A advisory bank as a boutique or a bulge bracket bank following the definitions provided by Wall Street Oasis (WSO), a leading job search forum for the financial services industry. Based on WSO's classifications, bulge bracket banks include Goldman Sachs, Bank of America Merrill Lynch, Citi, Morgan Stanley, etc. The rest are classified as boutique, including Lazard, Moelis & Co., Centerview, Greenhill, and Perella Weinberg.

Combining information from the above sources, we construct an individual-year panel detailing investment bankers' career paths and deal-advising histories. Since our model features a stationary equilibrium with time-invariant market shares for each sector, we construct our sample to be consistent with the this feature (Section 1.3). Over our sample period, the boutique sector was in expansion until 2006, after which its labor share stabilizes. We thus use the post-2006 data to match the sector-specific moments in estimating our model.[9] Our final sample covers the career trajectory of 4,299 bankers working for 135 M&A advisory firms, among which 14 are bulge bracket banks and the rest are boutique banks.

Deals in our sample differ in size and complexity. A larger and more complex deal requires more time and effort from investment bankers; it also offers more valuable learning opportunities for bankers and allows them to charge higher fees. To account for such heterogeneity across deals, we use fee-adjusted deal numbers (as opposed to simple deal counts) to measure bankers' output and track their human capital accumulation. This is because fees represent the compensation for skilled human capital input from bankers. Fees generally increase with deal size and complexity in a nonlinear fashion. We first model the relationship between fees and deal size, and extrapolate this relation to deals with missing fee data. The extrapolated fees provide a natural multiplier that reflects the amount of compensation for each deal. For deals involving multiple lead bankers, we equally divide the fee among them. We adjust a banker's deal numbers by applying this multiplier to each of his past deals. Internet Appendix C describes this measure in greater detail.

Table 1 presents descriptive statistics regarding banker and firm characteristics. We provide statistics for an individual-year panel to describe banker-level characteristics and for a bank-year panel to shed light on bank conditions. For a typical banker in our sample, there is around 4.5% likelihood that he will leave his current employment. The average banker has around 11 years of experience

[9] One drawback of restricting our sample to the post-2006 period is that there are only 12 years of data, and thus empirical moments, especially those pertaining to the persistence of variables, can be measured with greater noise using this short time series. We thus follow Lynch and Wachter (2013) and complement the sample with the data in 2001–2006 in constructing the non-sector-related moments. Lynch and Wachter (2013) show that utilizing the additional information in the auxiliary data helps improve estimation precision.

Table 1
Descriptive statistics

Variable	Sample	N	Mean	Median	Std dev.
Mobility	People-year	39,218	0.0449	0	0.2070
Tenure (years)	People-year	39,218	5.8503	4	5.5892
Experience (years)	People-year	39,218	10.7178	10	7.0998
Total deals	People-year	39,218	1.0425	0	3.2215
Deal value ($mil)	People-year	39,218	955.17	0	6,337.34
Number of bankers	Bank-year	1,259	31.1501	7	71.0862
Total deals	Bank-year	1,259	27.1882	2	61.9304
Deal value ($mil)	Bank-year	1,259	19,872.39	70	58,398.25

This table provides summary statistics for both the individual-level and the bank-level samples. In the individual-level sample, *Mobility* is an indicator for whether a banker leaves the current employer to join another in a given year. *Tenure* is the number of years a banker has worked in a firm. *Experience* is the total years of work experience of a banker. *Total deals* is the average deal volume of a banker in a given year (adjusted based on deal value). *Deal value* is the total value of the deals advised by a banker in a year, denominated in million dollars. In the bank-level sample, *Number of bankers* represent the number of bankers employed in the M&A division of a given bank-year. *Total deals* represent the average deal volume of the bank-year. *Deal value* is the total value of the deals advised by a bank-year.

and has worked in a given firm for 6 years. He advises around 1 deal per year, with an average value of about $955 million. The average bank in our sample employs about 31 bankers and advises a high volume of deals. The average deal volume is around 27 deals per year and $20 billion in value.

2.2 Identification and selection of moments

We estimate the model using the simulated method of moments (SMM), which chooses parameter values that minimize the distance between the moments generated by the model and their counterparts in the data. In this subsection, we present the data moments used in our estimation and explain how they help identify the model parameters.

In the initial step, we calibrate the value of some parameters that we can directly obtain from prior literature or measure in the data. Specifically, we set the discount factor β to be 0.9, a value commonly used in the literature. We set the exogenous exit rate, η, to 5% per year, to match the average dropout rate in the M&A advisory industry. We normalize the return on human capital for the bulge bracket sector, λ_0, to 1. Since value functions are scalable in the model, this normalization does not affect bankers' optimal career choices. The expected deal number in the Poisson process, m, and the learning function, $\ell(\cdot)$, jointly determine the speed of human capital accumulation and the path of future deals. Therefore, we can only identify the product of the scale parameter, ℓ, in Equation (12) and the linear coefficient, c, in Equation (3). We thus set c to be 1 and estimate other parameters subject to this normalization. We also set the likelihood of high match quality q to be 0.5, and thus we effectively discretize the match quality in the model based on the median of its empirical counterpart. Lastly, we set χ, the fraction of surplus captured by bankers in an employment pair, to 0.5. As discussed in Internet Appendix D, χ only affects bankers' wages, but not their career choices, and altering χ does not change

the real outcomes from the model or the values of the simulated moments we compute.

We estimate the remaining 9 parameters in an SMM system. These parameters include: λ_1, the return on human capital offered by boutique banks relative to that of the bulge bracket banks; $\{a, b\}$, which control for the slope and intercept of the expected deal number in Equation (3); ℓ, the overall speed of learning-by-doing; α, which controls for the return to scale of learning-by-doing; ρ, one minus the depreciation rate of human capital; $\{\delta_0, \delta_1\}$, which captures human capital nonportability in the bulge bracket and boutique sectors, respectively, as shown in Equations (5) and (6), and σ_ζ, the standard deviation of the match quality signal entrant bankers observe, as shown in Equation (11). Parameter identification in SMM requires choosing moments whose predicted values are sensitive to the model's underlying parameters. Our identification strategy ensures that there is a unique parameter vector that makes the model match the data most closely.

First, we use the average relocation rate within each sector to identify parameter σ_ζ. Within-sector relocation means that a banker switches from his current employer to another employer of the same type. In our model, the return on human capital λ and the portability parameter δ are identical across all employers in the same sector, and thus the trade-off between return and portability of human capital should not trigger a within-sector job change. Within-sector relocation is thus entirely driven by perceived match quality. If entrants observe signals with higher precision (and thus low σ_ζ), then their initial job choice is likely to be more accurate, leading to a low relocation rate within the sector.

Second, we identify the return on human capital offered by boutique banks, λ_1, using the net labor flow from the bulge bracket to the boutique sector. Recall that we normalize λ_0 to 1 for bulge bracket banks, and thus larger values of λ_1 suggest that, holding all else equal, human capital generates higher returns in the boutique sector, making boutique banks more attractive to prospective employees. In that case, we expect a larger fraction of bankers to transition from the bulge bracket sector to the boutique sector and thus a more positive net flow into the boutique sector. Since our model features risk-neutral agents, the estimated λ_1 should be interpreted as the "risk-adjusted" returns to human capital. That is, it reflects not only the pecuniary compensation earned by the employment pair but also the banker's risk appetite and other nonpecuniary preferences. To this end, we rely on the revealed preference approach in estimating λ_1: instead of using bankers' compensation data in both sectors that needs to be adjusted for risk and other nonpecuniary factors, we use bankers' career choices between the two sectors to infer the "risk-adjusted" returns offered by the two sectors.

Next, we use bankers' deal volumes to identify a and b, the slope and intercept coefficients of the expected deal number in Equation (3). The intercept, b, can be identified by the deal number of new entrants who have not

established any human capital, while the slope coefficient, a, can be identified using the deal volume of seasoned bankers. Higher a means that every unit of human capital generates more deals, thus increasing the number of deals advised by seasoned bankers relative to junior ones.

To identify α, which governs the curvature of bankers' learning process, we run the following regression using both the simulated and actual data:

$$n_{i,t} = \gamma_0 + \gamma_1 \cdot y_{i,t} + \gamma_2 \cdot y_{i,t}^2 + \varepsilon_{i,t}, \tag{14}$$

where y is the total years of a banker's working experience. In Equation (14), we expect that $\gamma_1 > 0$ and $\gamma_2 < 0$, and the combination of the two parameters helps us identify α. Intuitively, a high value of α manifests in a large concavity.

To identify how human capital accumulates and depreciates over time, we investigate the autocorrelation of a given banker's deal volumes over the previous 1–2 or 3–4 years:

$$n_{i,t} = \varrho_\tau \times \frac{n_{i,t-\tau} + n_{i,t-\tau-1}}{2} + \varepsilon_{i,t}, \tag{15}$$

where $\tau = \{1, 3\}$ denotes a 1-year lag and a 3-year lag, respectively, and $n_{i,t}$ is the number of deals advised by banker i in year t. The accumulation of human capital through learning-by-doing is the key mechanism that generates persistence in deal numbers in our model. If bankers learn slowly (ℓ is small), we expect the coefficients ϱ_1 and ϱ_3 to be low. In the extreme case in which $\ell = 0$, human capital does not accumulate and $m_{i,t}$ will always equal b in Equation (3). This implies that the deal number, $n_{i,t}$, follows an i.i.d Poisson process and exhibits zero autocorrelation, which yields $\varrho_1 = \varrho_3 = 0$. We use the average of the autocorrelation coefficients, $\frac{1}{2}(\varrho_1 + \varrho_3)$, to determine the learning speed ℓ.

The parameter ρ controls for the speed of human capital depreciation, with a higher (lower) value indicating slower (faster) decay. We use $\varrho_1 - \varrho_3$, the spread between ϱ_τ, to identify ρ. Intuitively, a smaller spread implies a higher value of ρ.

Last, we identify human capital nonportability δ_s by tracking a banker's deal volume over a [−3, +3]-year event window around his job transition.[10] How the deal volume evolves in this event window depends critically on two factors: a selection effect and a portability effect. The selection effect suggests that bankers who have experienced poor prior performance are more likely to switch jobs in search of better matches. The portability effect indicates that transitioning bankers will experience a decline in deal volume because of the loss of firm-specific human capital.

To capture these effects, we measure the changes in deal number for banker i around year t as:

$$\Delta n_{i,t} = \frac{n_{i,t+1} + n_{i,t+2} + n_{i,t+3}}{3} - \frac{n_{i,t-1} + n_{i,t-2} + n_{i,t-3}}{3}. \tag{16}$$

[10] This is because the deal arrival process can be lumpy, and we need more than 1 year to gauge bankers' productivity. Results are similar if we use a [-2, +2]-year window or [-4, +4]-year window.

We then regress $\Delta n_{i,t}$ on an indicator variable *Exit from Bulge Bracket* to gauge how a banker's productivity changes after he leaves a bulge bracket firm. *Exit from Bulge Bracket* equals one if banker i leaves a bulge bracket employer in year t and zero otherwise. Analogously, we run a separate regression of $\Delta n_{i,t}$ on an indicator *Exit from Boutique* to capture the effect of a banker departing a boutique firm.[11] Both regressions include current employer, next employer, and year fixed effects. These fixed effects help remove confounding effects coming from banks' intrinsic characteristics or macroeconomic conditions. A summary of how the moments are constructed is also available in Table 2.

Job transitions may lead to either increases or decreases in deal volume, depending on the relative strength of the selection and portability effects. When human capital is fully portable, the selection effect will always lead to an increase in the average post-transition deal volume, and it simultaneously determines the frequency of bankers' job transitions, which we also target in our estimation. As human capital becomes less portable, it leads to a

Table 2
Variable definitions

Variable/Moment	Definition
Relocation rate within the bulge bracket sector	The number of bankers transitioning from a bulge bracket bank to another bulge bracket bank divided by the total number of bankers employed by all banks
Relocation rate within the boutique sector	The number of bankers transitioning from a boutique bank to another boutique bank divided by the total number of bankers employed by all banks
Net labor inflow into the boutique sector	The difference between the number of bankers transitioning from a bulge bracket bank to a boutique bank and the number of bankers transitioning from a boutique to a bulge bracket bank, divided by the total number of bankers employed by all banks
Loading of deal number on avg. past 1- to 2-yr deal number	Coefficient obtained by regressing the number of deals advised by a banker in year t on the average number of deals advised by the same banker in $t-1$ and $t-2$, which is the coefficient ϱ_1 in Equation (15)
Loading of deal number on avg. past 3- to 4-yr deal number	Coefficient obtained by regressing the number of deals advised by a banker in year t on the average number of deals advised by the same banker in $t-3$ and $t-4$, which is the coefficient ϱ_3 in Equation (15)
Avg. deal number per banker per year	The average number of deals generated by each banker in a given year
Loading of deal number on banker years of experience	Coefficient obtained by regressing the number of deals advised by a banker in year t on the banker's total years of working experience as an M&A advisor, which is the coefficient γ_1 in Equation (14)
Loading of deal number on banker years of experience squared	Coefficient obtained by regressing the number of deals advised by a banker in year t on the square of the banker's total years of working experience as an M&A advisor, which is the coefficient γ_2 in Equation (14)
Avg. deal number per new entrant per year	The average number of deals generated by each new entrant in his/her first year as an M&A advisor
Deal num. chg. around banker transition from bulge bracket	Change in the 3-yr average deal number as a banker leaves a bulge bracket bank, as in Equation (16)
Deal num. chg. around banker transition from boutique	Change in the 3-yr average deal number as a banker leaves a boutique bank, as in Equation (16)

This table provides the variable definition. We use these variables as targeted moments in our SMM estimation.

[11] We exclude year t deals from this calculation to alleviate the concern that bankers may slow down right around job transitions or that they do not handle clients between jobs.

larger drop in deal volume following job transitions, which is captured by lower regression coefficients for the exit indicators. Therefore, we match the regression coefficients to identify the sector-specific portability measure, δ_s. Similar identification strategies have been used in the literature to estimate unobservable structural parameters, such as blockholders' fire sale discount (Albuquerque and Schroth 2015).

Figure 5 confirms that the above intuition is borne out by our model using the estimated parameters reported in Table 4. The figure illustrates how the perceived match quality, human capital, and the number of deals advised by a banker evolve as the banker switches from one employer to another. The left panel shows the results for bankers who leave bulge bracket firms, and the right panel shows the results for bankers who leave boutique firms. First, we note that the transitioning banker loses a significant fraction of human capital as he departs from the current bank (the dashed line with square markers), and the dip in human capital is particularly pronounced if his current employer is a boutique bank, reflecting that a larger fraction of human capital built in a boutique bank is firm-specific, that is, a stronger portability effect. This reflects the portability effect. Also note that perceived match quality gradually declines prior to the job change and jumps immediately following the transition (represented by the dash-dotted line with plus markers). This happens because a banker is more likely to switch jobs when his perceived match quality deteriorates, and once he joins a new bank, the match quality

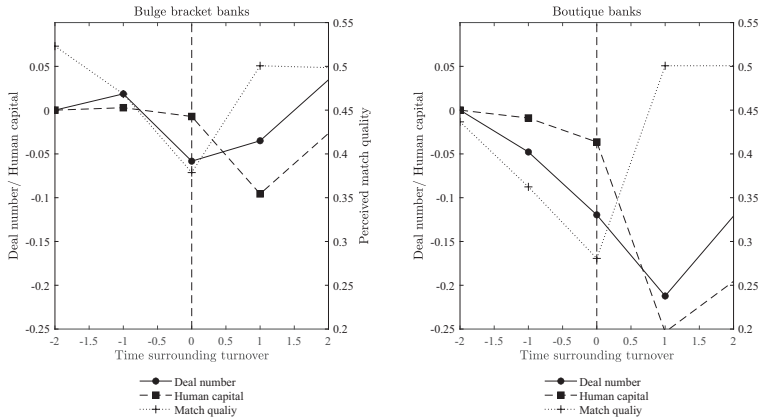

Figure 5
Changes around banker transitions
This figure shows changes in human capital, perceived match quality, and the number of deals advised by bankers when they switch jobs. The graphs are generated based on the parameters reported in Table 4. The left panel shows the results for bankers leaving bulge bracket firms, and the right panel shows the results for bankers leaving boutique firms. The solid lines with circle markers represent the evolution of deal numbers; the dashed lines with square markers represent the dynamics of human capital; and the dash-dotted lines with the plus markers trace the fluctuations in perceived match quality. The event window is centered on the transition year $t=0$. We normalize the human capital and deal number to zero for year $t=-2$, so the numbers can be viewed as the changes in human capital and deal number relative to those in year $t=-2$.

is redrawn. We also observe that the perceived match quality declines more prior to job switches of bankers working in boutique banks This is because the loss in nonportable human capital is more substantial when a banker leaves the boutique sector, and therefore, it requires even lower match quality to trigger a job transition. Combining the selection and portability effects, we find that for bankers leaving the bulge bracket sector, their deal number dips following a transition but rebounds quickly in the subsequent year. In comparison, the deal number of bankers who leave boutique banks drops much more, and the recovery is notably slower (as indicated by the solid line with circle markers). For these bankers, their deal volumes fall under the pretransition levels over the 3 years following transition.

3. Empirical Results

In this section, we present the parameter estimates and discuss their empirical implications. We then vary the estimated labor market frictions underlying the model and analyze alternative scenarios, quantifying the role of such frictions in shaping bankers' career outcomes and the production of financial services in the economy.

3.1 Model fit

Table 3 presents moments we target to match in the SMM estimation. The model is able to match most data moments closely. While labor mobility in the investment banking industry is higher than that in other industries, job switches are still rare events in this profession. Our model predicts that only 1.34% of bankers move from one bulge bracket bank to another per year. The

Table 3
Model fit

Moment	Empirical value	Simulated value	Standard errors
Relocation rate within the bulge bracket sector	0.0146	0.0134	0.0021
Relocation rate within the boutique sector	0.0168	0.0156	0.0011
Net labor inflow into the boutique sector	0.0082	0.0095	0.0013
Loading of deal numbers on avg. past 1- to 2-yr deal numbers	0.1511	0.1616	0.0201
Loading of deal numbers on avg. past 3- to 4-yr deal numbers	0.0803	0.0829	0.0259
Avg. deal number per banker per year	0.8034	0.7970	0.0366
Loading of deal numbers on banker years of experience	0.1269	0.1191	0.0042
Loading of deal numbers on banker years of experience squared	−0.0026	−0.0030	0.0002
Avg. deal number per new entrant per year	0.2145	0.2313	0.0205
Deal num. chg. around banker transition from bulge bracket	0.0952	0.0602	0.0334
Deal num. chg. around banker transition from boutique	−0.0967	−0.0583	0.0410

This table presents the empirical and simulated moments we target in our SMM estimation, along with the standard errors of the empirical moments. Model simulated moments are generated using the parameter values reported in Table 4. Details regarding the moment constructions can be found in Table 2.

relocation rate within the boutique sector is similar, about 1.56% per annum. These numbers line up well with their empirical counterparts, which are 1.46% and 1.68%, respectively. In addition, the model predicts that the net labor flow into the boutique sector accounts for 0.95% of all bankers in the industry, which is close to the 0.82% observed in the data.

Next, we examine bankers' deal volume. Consistent with the data, we find that Incumbents are more productive, advising on average of 0.8 deal per year, while entrants advise only 0.2 deal per year, due to their low human capital. Bankers' deal numbers are positively autocorrelated, and the magnitude of the autocorrelation declines with the horizon. Our model is able to capture these features. Specifically, the autocorrelation coefficient between the current and lagged 1- to 2-year (3- to 4-year) deal number is 0.16 (0.08) as predicted by the model, which is almost identical to the empirical counterpart of 0.15 (0.08).

Consistent with the data, the model predicts a concave relationship between deal number and bankers' total years of working experience: bankers advise more deals as they accumulate seniority, but the marginal benefit of learning-by-doing declines as the bankers gain more human capital over time. The model captures this concavity very well by accurately replicating both the linear and quadratic coefficients when we regress a banker's deal volume on his years of experience.

The model also closely matches the changes in deal volume around a banker's relocation. As we discuss in Section 2.2, this change is driven by two counteracting forces. First, prior to transitions, bankers may have encountered bad matches and generated low deal volumes. They expect the match quality to improve on average following a transition, and this selection effect contributes to an endogenous increase in deal number. Second, bankers lose their nonportable human capital, which needs to be rebuilt over time. This portability effect leads to an immediate decrease in the expected deal numbers post transition.

Insofar as human capital portability can differ across two sectors, we measure separately the changes in deal number for bankers who leave bulge bracket banks and those who leave boutique banks. In the model, bankers who depart from bulge bracket banks advise 0.06 more deal annually compared with their pretransition deal volume. This effect is economically sizeable given that an average banker advises 0.8 deal per year and the magnitude is comparable to the increase observed in the data (0.10). This positive change in post-transition deal volume also suggests that the selection effect dominates the portability effect among bulge bracket bankers, likely because they accumulate more generalizable skills. In contrast, bankers who depart from boutique banks experience a 0.06 decline in their post-transition deal volume as predicted by the model (the decline is 0.10 in the data). This result suggests that the loss of firm-specific human capital dominates the selection effect, making transition highly costly for employees in the boutique sector.

3.2 Parameter estimates

We report the parameter estimates in Table 4. Panel A presents the calibrated parameters. As discussed in Section 2.2, these parameters are less model-specific, so we calibrate them outside the model to ensure that our choices are consistent with the observed data characteristics and the consensus in the literature.

Panel B of Table 4 reports the point estimates and standard errors for the 9 parameters that we estimate via SMM. The standard deviation of the match quality signal, σ_ζ, is estimated to be 8.83, suggesting that the signal observed by entrants for their first job is likely quite noisy. This result implies that entrant bankers face a high level of uncertainty regarding match quality. Their ability to learn about match quality is thus critical for distinguishing good matches from bad ones ex post.

We estimate λ_1, the return to human capital offered by boutique banks, to be 1.033. Given that the return to human capital in bulge bracket banks, λ_0, is normalized to one, our estimate indicates that profit generated by each unit of human capital from deal advising is 3.3-percentage-points higher in the boutique sector. This is consistent with abundant anecdotal evidence that bulge bracket banks incur high overhead costs due to their large-scale and diverse operations, leaving lower profits to share with bankers. One caveat is that since λ_1 is identified based on the bankers' revealed preference through career transitions, it should be considered as bankers' perceived return to human capital, which is adjusted for other nonpecuniary factors, such as job stability, prestige, and private benefits derived from discretion and autonomy. Our λ_1 aims to capture, from bankers' perspective, the overall advantage of the

Table 4
Parameter estimates

A. Calibrated/normalized parameters

	Calibration		Normalization	
	β	η	λ_0	c
Value	0.9	0.05	1	1

B. Estimated parameters

	σ_ζ	λ_1	α	a	b	ℓ	ρ	δ_0	δ_1
Estimate	8.830	1.033	0.825	1.040	0.223	0.310	0.889	0.116	0.459
Standard errors	4.142	0.009	0.118	0.224	0.015	0.043	0.078	0.062	0.113

In this table, we report the parameter estimates. Panel A displays the parameters calibrated or normalized. Panel B displays the parameter estimates obtained from the SMM, together with the estimation standard errors. β is the discount rate, η is the exogenous exit rate of bankers, λ_0 is the return to human capital in bulge bracket banks, c controls for the expected deal number in Equation (3), σ_ζ is the standard deviation of the match quality signal observed by entrants, λ_1 is the return to human capital in boutique banks, α controls for the decreasing marginal benefits of learning-by-doing in Equation (12), a and b are the slope and constant coefficients in Equation (3) that determine the expected deal number, ℓ is the parameter that controls the speed of learning-by-doing in Equation (12), ρ is the persistence of human capital (one minus the depreciation rate), and δ_0 and δ_1 are human capital nonportability in the bulge bracket and boutique sectors, respectively.

boutique sector relative to the bulge bracket sector in utilizing human capital and attracting bankers.

The slope coefficient in Equation (3), a, is estimated to be 1.04. Given that we normalize c to one in the equation, this estimate suggests that the expected deal number produced by a good match ($\mu = 1$) doubles that produced by a bad match ($\mu = 0$). This finding highlights the importance of match quality. Note that higher match quality not only increases the expected number of deals advised within each period but also influences the speed of human capital accumulation and propels future deal generation. The effect of high match quality, therefore, is amplified and persists in the long run. The constant parameter in Equation (3), b, is estimated to be 0.223. This parameter determines the average number of deals advised by novice bankers in their first year of employment.

Our estimate of human capital persistence, ρ, is 0.889, implying that about 11% of human capital becomes obsolete each year, similar to the depreciation rate of physical capital documented in the literature.

Last, we find that human capital portability differs significantly across the bulge bracket sector and the boutique sector. Based on our estimates, 88% of the human capital that bankers accumulate in bulge bracket firms is portable and only 12% is nonportable. However, only 54% of the human capital acquired by boutique firm employees is portable. This stark difference in human capital portability, paired with the difference in the return to human capital they offer, constitutes the main trade-off that bankers face in making career choices between bulge bracket and boutique firms.

3.3 Validation of estimation results

In this section, we conduct more exercises to verify the model's fit in other dimensions that are not explicitly targeted in the SMM estimation. First, we compare the relation between a banker's mobility rate and the years of experience in the model and in the data. Our model predicts that labor mobility decreases with experience for two reasons. First, senior workers are more likely to be a good match with their current employers after a long course of learning and searching for good employment opportunities. This means that they are less likely to move in future periods as they have settled down. Second, bankers who have a long tenure with their employers accumulate more nonportable human capital, and the potential loss of firm-specific skills makes their job transitions particularly costly. Figure 6 confirms the above prediction and shows a strong negative relationship between a banker's mobility rate and the years of experience—as experience increases from 1 to 5 years to over 30 years, the expected annualized mobility rate decreases from over 7.3% (6.8%) to about 1.5% (1%) in the model (the data). These results provide useful validation of our model as they pertain to important trade-offs in bankers' career decisions and emerge as the central predictions of the model.

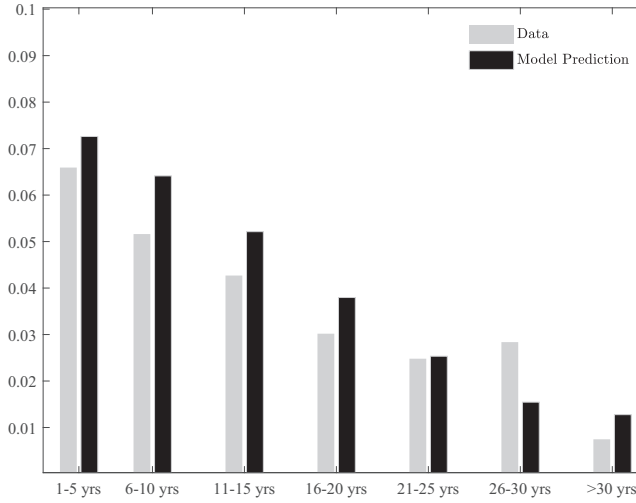

Figure 6
Mobility and banker seniority
This figure illustrates the relationship between banker mobility and seniority. We partition bankers into seven groups based on their years of working experience and compute the average mobility rate within each experience group. The mobility rate is defined as the likelihood of a banker leaving the current employer and joining a new employer. The black bars represent the mobility rate implied by the model, and the gray bars represent the mobility measured in the data.

Second, we calculate the boutique sector's labor share as predicted by the model. As reported in Table 4, the bulge bracket and boutique sectors differ in both the return to human capital ($\{\lambda_0, \lambda_1\}$) and the portability of human capital ($\{\delta_0, \delta_1\}$). Our model predicts that 53% of bankers choose to work for the boutique sector. This number matches the boutique sector labor share that we observe in the data, which is about 57%.[12]

Lastly, we go one step further and ask, can our model match not only the average labor share of boutique banks but also the composition of labor across different experience cohorts? More specifically, our model predicts that more experienced bankers are more likely to move from bulge bracket to boutique banks, and this generates a unique pattern between bankers' experience and their sector choices. To verify this prediction in the data, we compute the boutique sector labor share within each banker experience cohort. We find a significant and positive slope (0.77) of the experience-boutique labor share relation. The result closely matches the slope coefficient that we would obtain from the model-simulated data (0.92). To put these numbers in perspective, it suggests that bankers with 15 years of experience are 9-percentage-points more likely to be part of the boutique sector than those with 5 years of experience.

[12] The boutique labor share is calculated using data post-2006, when the share has stabilized.

3.4 Dissecting labor market frictions

In this section, we use the estimated model to dissect the effects of various labor market frictions on bankers' career choices and aggregate productivity. We vary the parameters that govern the nonportability of human capital and the match quality uncertainty in the model and examine how the model implications change with the underlying frictions. We compare the implications with those obtained from the baseline scenario to assess the effect of these frictions quantitatively. In particular, we compare the effect of nonportability against that of uncertain match quality, as the latter has been shown to be a primary driver of the mobility and productivity of workers (Jovanovic 1979; Flinn 1986; Fredriksson, Hensvik, and Skans 2018). This comparison allows us to effectively assess whether human capital portability materially influences the banker-level and aggregate outcomes.

We investigate two hypothetical cases of human capital portability: first, we reduce the nonportability of human capital ($\{\delta_0, \delta_1\}$) by 50%, which we label as the "Enhanced portability" case; next, we eliminate portability friction completely, so that $\delta_0 = \delta_1 = 0$, and we label this as the "Perfect portability" case. In this latter case, bankers suffer no loss of human capital following job transitions. We focus on four key variables: labor mobility rate, boutique sector labor share, bankers' human capital stock, and financial service production. Labor mobility rate is defined as the number of bankers who switch jobs in a given year divided by the total number of bankers in the model economy; boutique labor share is defined as the number of bankers employed in the boutique sector divided by the total number of bankers in the model economy; human capital stock is the sum of portable and nonportable human capital possessed by individual bankers; and financial service production equals the sum of the present value of deals advised by all bankers. It measures the aggregate production of financial services in the model economy.

Panel A of Table 5 reports the results. In row 1, we report the values of the key variables in our baseline scenario. Rows 2 and 3 report the corresponding values obtained from the enhanced and perfect portability cases, respectively. Comparing results for banker mobility across these scenarios, we find that human capital portability significantly affects labor mobility. With perfect portability, job changes become less costly to bankers and they explore outside options more frequently, leading to a 32% $\left(= \frac{0.082 - 0.062}{0.062}\right)$ increase in labor mobility.

Importantly, enhanced human capital portability leads to greater value of financial services being created. Given the estimated degree of human capital nonportability, it would reduce M&A advisors' human capital by 3.4% ($= \frac{1.3516 - 1.3068}{1.3068}$). Notably, the portability friction generates more pronounced effects in the sector that generates higher return. Thus, the total value of deal advising services is reduced even further by 5.1% ($= \frac{1.1039 - 0.9922}{0.9922}$). Moreover, these numbers are likely to represent a lower bound, because the

Table 5
Human capital portability and labor market outcomes

A. Portability and information

	Mobility (%)	Boutique share (%)	Human capital	Financial service production
(1) Baseline	6.19	52.88	1.3071	9.9334
(2) Enhanced portability	7.19	72.38	1.3099	10.1173
(3) Perfect portability	8.23	100.00	1.3516	10.4279
(4) Enhanced information	5.18	47.12	1.3415	10.4862
(5) Perfect information	4.77	42.98	1.3812	11.0380

B. Effect of perfect portability over career stages

Years of experience	1–5 yr	6–10 yr	11–15 yr	16–20 yr	21–25 yr	26–30 yr	31–35 yr	36–40 yr
△ Mobility	−1.962%	4.136%	4.079%	3.655%	3.246%	2.780%	2.458%	1.692%
$\frac{\triangle \text{Human capital}}{\text{Human capital}}$	1.418%	2.923%	4.330%	4.776%	4.626%	4.214%	3.697%	2.294%
$\frac{\triangle \text{Fin. serv. production}}{\text{Fin. serv. production}}$	5.209%	6.042%	6.195%	5.951%	5.473%	4.997%	4.461%	2.592%

This table compares the outcomes from the baseline model and those from alternative scenarios where we reduce or eliminate portability frictions and match quality uncertainty. In panel A, we consider four scenarios in addition to the baseline. "Enhanced portability" and "Perfect portability" correspond to cases in which we reduce the nonportability of human capital $(\{\delta_0, \delta_1\})$ by 50% and 100%, respectively. "Enhanced information" and "Perfect information" represent cases in which we assume that the true match quality is revealed to any firm-banker pair once the pair is formed with a probability of 50% and 100%, respectively. In each case, we examine bankers' mobility (the likelihood of job switches), boutique share (the share of bankers employed by the boutique sector), human capital stock, and financial service production (i.e., we take all existing bankers in the economy and calculate the present value of the service they create, $\Sigma\left(\beta^t \pi_t\right)$ in all future periods). In panel B we explore the extent to which the impact of perfect portability changes over bankers' career stages by partitioning bankers into groups into every 5-year interval of working experience. We compute the changes in bankers' mobility, human capital stock, and financial service production in each of the hypothetical cases relative to their values in the baseline case. We report the change in labor mobility, and the percentage changes in human capital stock and financial service production.

calculation only accounts for the effect of employees' job switches on their own productivity. Portability frictions can also generate a negative spillover effect — job switches can break up teams and further reduce the productivity of other bankers.

Lastly, the results suggest that human capital portability has an important influence on bankers' sectoral choices. As portability increases, bankers are less concerned about losing human capital during job transitions and are more inclined to join the sector that offers a higher return on human capital (λ). This sharply increases boutique banks' labor share. Specifically, When the human capital nonportability is reduced by a half (row 2), boutique banks will gain an additional 20% of labor share. In the extreme case of fully portable human capital (row 3), the boutique sector dominates the labor market.

We perform the same analysis for match quality uncertainty, assuming that the true match quality is revealed with a given probability after the formation of any employment pair. We set this probability to 50% and 100% in the "Enhanced information" and "Perfect information" cases, respectively. Rows (4) and (5) report results for these cases. We note that the effects of human capital portability on human capital accumulation and financial service production are comparable to that of uncertain match quality. This comparison

suggests that firm-specific human capital is a quantitatively important friction for bankers' career choices.[13]

Our analysis above quantifies the importance of human capital portability for an average banker's mobility and performance. Next, we explore how the effect varies over bankers' career stages. To do so, we partition bankers based on their career stages (years of working experience) into 5-year intervals and calculate the changes in labor mobility, human capital stock, and financial service production between the perfect portability scenario and the baseline scenario at every stage.[14] Results are reported in panel B of Table 5. Changes in mobility, that is, $\triangle$Mobility, are reported directly in percentage points while changes in human capital and financial service production are scaled by the baseline value, that is, $\frac{\Delta\text{Human capital}}{\text{Human capital}}$ and $\frac{\Delta\text{Fin. serv. production}}{\text{Fin. serv. production}}$.

Results in panel B suggest that enhancing human capital portability promotes bankers' mobility at all career stages except for the most junior bankers whose mobility declines. This occurs because perfect portability has two counteracting effects on mobility: first, perfect portability makes job transition costless, which stimulates mobility (the stimulating effect); second, since bankers are not concerned with human capital loss upon job changes, they become more patient in learning about match quality, which delays job switches (the option of "waiting"). For most junior bankers, the option of waiting dominates the stimulating effect, and therefore, they postpone their job switches to later career stages. Accordingly, we observe a large increase in mobility for the subsequent 10-year period. The effect of perfect portability on mobility remains positive but decays over the long run, leading to a hump-shaped relation between change in mobility and banker career stages. Similar hump-shaped relationships also arise when we examine bankers' human capital accumulation and financial service production. For example, bankers with 6–20 years of experience would produce 6% more financial service if their human capital became fully portable. Such gains, though positive, become much smaller for very junior and very senior bankers.

Such hump-shaped effects suggest that in the baseline model, mid-career bankers suffer most heavily from the lack of human capital portability. Many of those bankers have started to realize that their employers are not good matches and hope to move. Yet, job changes are highly costly because they have accumulated substantial firm-specific human capital. In comparison, junior and senior bankers benefit to a lesser extent from having perfect portability, because junior bankers have little firm-specific human capital, and therefore they have

[13] Note that better information about match quality reduces mobility. This is because better information allows bankers to be informed about current match quality and are able to make more timely job separation decisions. Such decisions are also more accurate and less prone to mistakes. As a result, bankers do not need to switch jobs as frequently.

[14] We leave out the boutique banks' labor share in this exercise, because as shown in panel A of Table 5, when human capital is perfectly portable, bankers always choose to work in the boutique sector regardless of their career stages.

little to lose in job transitions. Senior bankers are more likely to have found good matches and have less desire to change jobs.

4. Sources of Nonportable Human Capital

Our baseline model estimation suggests that a substantial fraction of bankers' human capital is firm-specific and nonportable, and the nonportability varies across firms with different organization structures. In this section, we investigate two potential sources of nonportability— industry expertise and within-firm collaboration.

4.1 Industry expertise and job compatibility

Investment bankers accumulate human capital and develop both general and specific skills through deal-making. One important aspect of the specific skills is developed through learning about the clients' industry, such as the regulatory environment, product market competition, and industry structure. Industry expertise is often advertised by M&A advisory firms as a competitive advantage over their peers, and expertise in one industry usually cannot be directly applied to another industry. General skills, in contrast, are often developed through learning the common features of M&A deals across different industries, and thus bankers accumulate more general skills when exposed to deals in multiple industries. In this regard, a bank's industry coverage plays an important role in determining the composition of its employees' skills and how portable these skills are.

To explore this mechanism, we start by characterizing the industry coverage for each employer. We first classify all M&A industries into five categories: (1) manufacturing, (2) transportation, (3) FIRE, that is, financial, insurance, and real estate, (4) services, and (5) others, which include agriculture, wholesale and retail, mining and construction, and public administrative.[15] Based on this industry classification, each employer is assigned a binary vector indicating its industry coverage in the past five years. Suppose a firm covered only the first three industries in the past five years, the firm's industry coverage vector is $[1,1,1,0,0]$ as of year t.

For each banker, we define an industry compatibility measure between his current and future employers. This measure is intended to gauge how general the banker's skills are from the current employer and how easily these skills can be applied to his next employment. Suppose firm A has an industry coverage vector $v_a = [1,1,1,1,1]$, firm B has $v_b = [1,1,0,0,0]$, and firm C has

[15] The fifth category comprises various sectors, each with limited deals. Using a more detailed industry classification poses challenges due to computational limitations. This is because the total number of possible industry coverage equals 2^N, where N is the number of industries we define. Since industry coverage is a state variable in the extended model, a large N renders the model substantially slower to solve. Moreover, given that each industry in the last category has relatively few deals, many firms will have zero coverage of these industries. Consequently, the gain from explicitly modeling these industries will be limited.

$v_c = [0, 1, 1, 0, 0]$. Bankers working in firm A develop skills that can be applied to all five industries, while bankers working in firm B or C develop skills in the industries their employers specialize in. Thus, bankers in firm A have more general human capital, and less firm-specific human capital. Therefore, when they move from firm A to firm B or C, all their human capital is portable because their skills can be applied to all industries covered by the new employers. In contrast, bankers moving from firm B to firm C lose some human capital because their human capital cannot be applied to Industry 3.

To formally capture this idea, we construct the compatibility measure by counting the number of overlapping industries between the current and the new employers and scaling it by the number of industries of the latter:

$$\text{Compatibility}_{a \to b} = \frac{v_a \cdot v_b'}{\text{Industry Coverage}_b}, \tag{17}$$

where *Industry Coverage* is the total number of industries covered by a bank. In the above example, *Industry Coverage* equals 5 for firm A, 2 for firm B, and 2 for firm C. For bankers moving from firm A to firm C, the compatibility measure is 100% ($= \frac{[1,1,1,1,1] \cdot [0,1,1,0,0]'}{2}$), implying that they have expertise in all the industries covered by firm C. For bankers moving from firm B to firm C, the compatibility measure is 50% ($= \frac{[1,1,0,0,0] \cdot [0,1,1,0,0]'}{2}$), implying that only half of their skills are useful to firm C. A higher compatibility measure therefore implies a higher portability of banker human capital in job transition.

We examine the relationship between compatibility and human capital portability in the data. Specifically, we regress the changes in deal number, defined in Equation (16), on the interaction between an indicator for job transitions (*Exit*) and the quartile ranking of the compatibility measure between the current and next employers. The regression controls for fixed effects for the current employer, the next employer, and the year. Such fixed effects are used to purge out the confounding effects related to firm characteristics and macro conditions that may be present in the data, but not in the model. We find that *Exit* × *Compatibility* generates a significant positive coefficient of 0.1, indicating that the changes in bankers' productivity around job transitions are positively correlated with the compatibility between two employers.

Motivated by the empirical evidence, we extend the baseline model to incorporate the relationship between industry coverage and human capital portability. In this extension, we drop the sector label, s, and replace it with a new state variable that captures firms' industry expertise. This specification allows us to specify bankers' human capital portability as a function of industry expertise, which helps micro-found the cross-sector portability gap documented previously. More specifically, we write:

$$\delta = \delta_0 + \delta_1 \times (1 - \text{Compatibility}), \tag{18}$$

where *Compatibility* measures the industry overlap between the past and the new employers, as defined in Equation (17); δ_0 captures the human capital

loss upon job transition even if two employers have 100% overlap in industry coverage (and thus a compatibility of 1), and δ_1 captures the incremental effect of compatibility on portability.

Since we drop the sector labels, we also reparametrize the return to human capital, λ, as a function of industry coverage:

$$\lambda = \lambda_0 + \lambda_1 \times \text{Industry Coverage}, \tag{19}$$

where λ_0 is normalized to one as in the baseline model, and the parameter λ_1 thus captures how a bank's industry coverage influences the profit from each deal it generates. Anecdotal evidence suggests that banks specializing in a small number of industries can operate more efficiently and incur lower overhead costs.

To estimate the new parameters, we revise the moments used for identification. Following a similar intuition as in Section 2.2, we use observed deal number changes around banker job transitions to pin down parameters related to portability, while replying on labor mobility to identify the revealed efficiency. Specifically, we target the regression coefficient of deal number change on the *Exit* indicator to identify δ_0, and use the regression coefficient for *Exit* $\times$ *Compatibility* to identify δ_1. Finally, we regress a banker's mobility on his employer's industry coverage and use the regression coefficient to identify λ_1.

Table 6 reports the estimation results. The extended model provides a good fit for the moments, and our estimates for δ_1 suggest that an interquartile increase (0.46) in industry compatibility leads to a 17.8-percentage-point increase in the human capital portability when advisors switch jobs ($=0.386 \times 0.46$).

4.2 Collaboration and team capital

The second source of firm-specific human capital that we examine is within-firm collaboration. In the modern U.S. economy, tasks are often assigned to teams and accomplished by a group of workers (Lazear and Shaw 2007; Baghai, Silva, and Ye 2019). Working in teams helps individuals develop complementary skills and effectively coordinate with one another during the production process. Teamwork is particularly important in the financial services industries, where deals are often organized through syndicates and underwritten by a group of bankers. M&A advisory is no exception. Many bankers repeatedly collaborate with colleagues, sharing expertise and jointly advising their clients. For these banks, job transitions should be costlier as they need to sever ties with a well-fit team. In contrast, bankers who work more independently and collaborate less within firms should be more adaptive to new employers.

We extend our baseline model to incorporate the idea that team collaboration leads to nonportable human capital. We start by constructing a measure of collaboration intensity at the banker-firm level. For each individual banker in

Table 6
Industry coverage and human capital portability

A. Model fit

Moment	Empirical value	Simulated value	Standard errors
Avg. relocation rate	0.0550	0.0534	0.0010
Regression coefficent of labor mobility on industry coverage	0.0069	0.0070	0.0010
Loading of deal numbers on avg. past 1–2 yr deal numbers	0.1511	0.1771	0.0137
Loading of deal numbers on avg. past 3–4 yr deal numbers	0.0803	0.0852	0.0177
Avg. deal number per banker per year	0.8034	0.7987	0.0251
Loading of deal numbers on banker years of experience	0.1269	0.1192	0.0029
Loading of deal numbers on banker years of experience squared	-0.0026	-0.0030	0.0001
Avg. deal number per new entrant per year	0.2145	0.2545	0.0140
Regression coefficient of deal number change on exit	-0.2418	-0.2725	0.1340
Regression coefficient of deal number change on exit*compatibility	0.1007	0.0744	0.0540

B. Parameter estimates

	Calibration		Normalization	
	β	η	λ_0	c
Value	0.9	0.05	1	1

	σ_ζ	λ_1	α	a	b	ℓ	ρ	δ_0	δ_1
Estimate	8.055	-0.003	0.843	1.650	0.250	0.249	0.871	0.008	0.386
Standard errors	3.880	0.003	0.276	0.740	0.015	0.079	0.055	0.110	0.089

In this table, we report the model fit (panel A) and the parameter estimates (panel B) for the extended model that allows a banker's human capital portability to depend on the compatibility of industry coverage between the current and the next employers. In panel A, the first two moments correspond to the overall mobility among bankers and the regression coefficient of mobility on industry coverage; the next six moments are the same as those in the baseline (reported in Table 3); the last two moments correspond to the regression coefficient obtained from regressing the deal number change of a banker on the dummy of job switch (*Exit*) and the coefficient from regressing the deal number change on the interaction between the *Exit* dummy and the quartile of the compatibility measure, respectively. In panel B, the parameters λ_0 and λ_1 are defined in Equation (19), the parameter δ_0 and δ_1 are defined in Equation (18), and other parameters are defined as in the baseline model.

an advisory firm, we first define the number of collaborations as the count of deals the banker has coadvised with his colleagues since he joined the bank. If the banker coadvised two deals with the same colleague, we count them as two collaborations because these experiences strengthen the banker's relationship with this colleague. The total number of collaborations is then normalized by the total number of M&A bankers working in the advisory firm so that we measure the average strength of a banker's synergy with his colleagues. We refer to the resultant ratio as "collaboration intensity." Collaboration intensity is specific to an individual banker-firm pair. Higher collaboration intensity is expected to reduce the portability of a banker's human capital. To keep the notations consistent with *Compatibility*, we define *Banker Independence* as *1 - Collaboration Intensity*.

In parallel to the industry expertise analysis, we regress the changes in banker productivity around job transitions on the interaction of *Exit* and *Banker Independence*, controlling for the same set of fixed effects. We obtain a coefficient of 0.114 on the interaction term, suggesting that bankers who work independently and have weaker ties with their colleagues experience less decline in productivity in job transitions compared to other bankers.[16]

To fit these observed data features and illuminate the underlying driving forces, we extend our baseline model to incorporate collaboration intensity. We use a similar setting as in Section 4.1: we drop the sector labels and specify the nonportability of human capital, δ, and the return to human capital, λ, as functions of banker independence (lack of collaboration):

$$\delta = \delta_0 + \delta_1 \times (1 - \text{Banker Independence}), \tag{20}$$

$$\lambda = \lambda_0 + \lambda_1 \times \text{Banker Independence}, \tag{21}$$

where δ_1 and λ_1 capture how the nonportability and return to human capital depend on our measure of banker independence. In data, anecdotal evidence suggests that high collaboration intensity (and thus low independence) forms team capital, which may enhance productivity (e.g., efficiency in deal advising) but render human capital more team-specific. In our estimation, however, we impose no prior and allow the data to guide the estimates of these parameters. To estimate the new parameters, we use the average deal number change around job switches to pinpoint δ_0, and we use the correlation between deal number change around job switches and the measure of banker independence obtained from the above-mentioned regression to identify δ_1. We again normalize λ_0 to be one and estimate λ_1 using the correlation between the likelihood of job switch and banker independence.

Table 7 presents the estimation results. The model closely matches the data moments, including the new ones we introduce to identify the connection between workers' collaboration and the portability and turn of their human capital. We estimate δ_1 to be 1.322, indicating that an interquartile (0.14) increase in banker independence is associated with an 18.5-percentage-point increase in human capital portability. The magnitude of this effect is comparable to that observed from differential industry coverage, as reported in Table 6. This implies that both firms' organizational structure and workers' collaboration style are equally pivotal in determining the portability of their human capital. Furthermore, we note that banker independence and industry coverage are only weakly correlated, which underscores that the mechanisms we investigate are driven by distinct economic factors and do not significantly overlap.

[16] We exclude from the sample a small set of observations where bankers colocate with their team members to the next employer. This ensures that job transitions are always accompanied by team breakups.

Table 7
Team collaboration and human capital portability

A. Model fit

Moment	Empirical value	Simulated value	Standard errors
Avg. relocation rate	0.0550	0.0534	0.0010
Regression coefficent of labor mobility on bank independence	0.0086	0.0084	0.0010
Loading of deal numbers on avg. past 1–2 yr deal numbers	0.1511	0.1717	0.0137
Loading of deal numbers on avg. past 3–4 yr deal numbers	0.0803	0.0876	0.0177
Avg. deal number per banker per year	0.8034	0.8024	0.0251
Loading of deal numbers on banker years of experience	0.1269	0.1202	0.0029
Loading of deal numbers on banker years of experience squared	-0.0026	-0.0030	0.0001
Avg. deal number per new entrant per year	0.2145	0.2466	0.0140
Regression coefficient of deal number change on exit	-0.2687	-0.2561	0.0830
Regression coefficient of deal number change on exit*bank independence	0.1140	0.0697	0.0280

B. Parameter estimates

	Calibration		Normalization	
	β	η	λ_0	c
Value	0.9	0.05	1	1

	σ_ζ	λ_1	α	a	b	ℓ	ρ	δ_0	δ_1
Estimate	6.654	-0.012	0.843	1.272	0.242	0.286	0.879	0.063	1.322
Standard errors	2.537	0.072	0.212	0.457	0.015	0.062	0.047	0.144	0.537

In this table, we report the model fit (panel A) and the parameter estimates (panel B) for the extended model that allows a banker's human capital portability to depend on his collaboration intensity with colleagues. In panel A, the first two moments correspond to the overall mobility among bankers and the regression coefficient of mobility on banker independence (1-collaboration intensity); the next six moments are the same as those in the baseline (reported in Table 3); the last two moments correspond to the regression coefficient obtained from regressing the deal number change of a banker on the dummy of job switch (*Exit*) and the coefficient from regressing the deal number change on the interaction between the *Exit* dummy and the quartile of the banker independence measure. In panel B, the parameters λ_0 and λ_1 are defined in Equation (21), the parameter δ_0 and δ_1 are defined in Equation (20), and other parameters are defined as in the baseline model.

4.3 Discussion of the mechanisms

In this section, we examine two important dimensions of heterogeneity: the difference in industry coverage across firms and the distinct collaboration style among bankers. Our estimation suggests that both factors are crucial determinants of human capital portability, and they also have sizeable effects on the productivity of employment pairs.

These mechanisms also help us understand the estimated gap in human capital portability across bulge bracket and boutique firms, as they differ in both industry coverage and collaboration intensity. While bulge bracket banks tend to have full industry coverage, boutique banks often specialize in only one or two industries. As a result, industry compatibility is higher for job transitions from the bulge bracket sector, compared to the transitions from boutique firms. Meanwhile, bankers in the bulge bracket sector have a much

lower collaboration intensity than those working in the boutique sector (0.04 vs. 0.29), potentially because of the expansive business scope of bulge bracket firms. Taken together, industry specialization and within-firm collaboration likely contribute to the low human capital portability in boutique firms.

5. Robustness Checks

Our baseline model captures endogenous job transitions as an outcome of bankers' learning and the costs they face from the nonportability of human capital. To make the model tractable and estimable, we simplify other dimensions of bankers' career decisions. In this section, we discuss the implications of several elements left out of the baseline model and perform additional estimations to verify the robustness of our main results.

In our baseline model, we assume that banks have homogeneous production functions as specified in Equation (3). In this section, we extend the model by allowing bulge bracket and boutique firms to have heterogeneous production functions. An additional benefit of doing so is that it allows us to more accurately model the selection effect. In this way, we can better isolate the selection effect from the observed deal number changes around job transitions, quantifying the sector-specific portability. Specifically, we modify parameter a to be sector-specific, represented as a_s, where $s \in \{0,1\}$ denotes the bulge bracket or boutique sector. We focus on the heterogeneity in a because it determines the strength of the selection effect: a larger a_s means a banker's productivity is more sensitive to his match quality. Hence, if the banker leaves a poorly matched employer, he should experience a greater productivity boost, representing a stronger selection effect. A larger a_s also implies higher productivity dispersion across advisors with good and bad match quality, even conditional on their human capital levels. Consistent with this intuition, we find that the volatility of boutique bankers' annual deal numbers is 27% higher than that of bulge bracket bankers. Given this finding, we estimate the extended model to match the original set of moments we use in the baseline model estimation, together with the differential deal volatility across sectors. Our results confirm the conjecture that boutique bankers indeed face a_s that is 18% higher than bulge bracket bankers. We also note that other parameter estimates remain quantitatively similar to their baseline estimates, with the portability gap $(\delta_1 - \delta_0)$ slightly widened. This indicates that our baseline model estimation is robust to allowing for heterogeneous investment opportunities across sectors.

In the baseline model, we also assume that match quality remains unchanged for each employment pair once formed. One may argue that match quality can improve if the banker is adaptive and gradually fits into the organization, or if teamwork synergies take hold over time. As the second extension, we assume that match quality is time-varying for a given banker and firm, and it improves at an exogenous rate of x each period as long as the banker stays in the current

firm. All agents can perfectly anticipate this effect. Accordingly, we revise the belief-updating process in Equation (7) as follows:

$$p_{i,b,t+1} = P\{\mu_{i,b} = 1 | N_{i,b,t} = N; p_{i,b,t}\} \cdot (1 - x) + x. \tag{22}$$

To quantify how the time-varying match quality affects our conclusions, we reestimate the model by setting $x = 2\%$. This leads to about 20% higher probability that a banker becomes a good match with his employer after working there for 10 years, a value we consider plausible in the real world. Our estimates stay largely robust under this alternative specification, suggesting that a modest speed of improvement in match quality does not change our results quantitatively.

Next, we discuss scenarios with endogenous exits. In our baseline model, bankers have a 5% likelihood of permanently leaving the industry, and the exit rate is uncorrelated with banker characteristics. We now consider two alternative scenarios where the exit rate can be contingent on bankers' characteristics. First, bankers with excellent records may be promoted to higher-level positions less involved with deal-making, or move to private equity or hedge funds. Second, bankers who constantly underperform may get "washed out" of the industry. These cases suggest that bankers with very high or very low human capital are more likely to disappear from our sample. To test the robustness of our results to these scenarios, we augment our baseline model by imposing an upper bound and a lower bound on banker human capital: $\bar{H}$ and $\underline{H}$. More specifically, we assume that a banker is promoted and exits the sample when his human capital reaches $\bar{H}$, in which case he obtains a high terminal utility $\bar{U}$. Alternatively, a banker is eliminated from the industry when his human capital drops below $\underline{H}$. A fired banker has an expected utility that equals his outside option, which we normalize to 0. We choose the values of the thresholds, $\bar{H}$ and $\underline{H}$, so that the model generates a 2% promotion rate and a 2% elimination rate annually. We reestimate the extended model, and our parameter estimates remain similar to our baseline results.

Another consideration is that we do not explicitly model the effects of noncompete clauses on bankers' careers. While bankers may face restrictive covenants in their employment contracts, the main reason that investment banks impose those covenants is to retain key clients after banker departures. In New York and California, stringent noncompete clauses face tough court battles, and employers may be deemed "unreasonable" on legal grounds (Peters 2019; Naidu, Posner, and Weyl 2018). In addition, we note that noncompete clauses are often of relatively short duration, between 6 months to a year (Landau 2016). In our estimation, we take into account the potential effects of noncompete clauses by excluding the year of job transition when we calculate deal number changes in Equation (16). As another robustness check, we further account for the effects of noncompete clauses by excluding bankers with unemployment spells of longer than 12 months. We conjecture that a combination of binding noncompete clauses and labor market search

and matching frictions might have contributed to these longer-than-usual unemployment spells. After removing these cases, we find that relocating bankers, on average, experience a change in the deal number of 0.121 (−0.066) around the transitioning year for the bulge (boutique) sector, which aligns closely with the targeted moments in our baseline estimation.

The Global Financial Crisis (2007–2009) represents a period of extreme distress for the financial industry, accompanied by significant shrinkage in M&A deal volume and large-scale labor relocation. To ensure that our results are not driven by this special period, we exclude this period from our sample so that our key identifying moments (e.g., declines in deal volume after job transitions) are not influenced by the Crisis. We reestimate our model by matching the data moments calculated using the noncrisis years, and our parameter estimates remain robust.

In our estimation, we calibrate the exogenous exit rate to be 5%, the average value in our sample. To assess how sensitive our estimation is with respect to this parameter, we vary it in the range of 3% to 7% and reestimate the model to fit the data. Our findings indicate that the parameter estimates, particularly the nonportability measures, remain stable across various exit rate values.

Estimation results of these alternative models and using alternative sample constructions are reported in Internet Appendix E.

Lastly, in our baseline model, we refrain from discussing any implications on wage dynamics. The model assumes an efficient bargaining environment in which a firm and a worker stay matched as long as the joint surplus of doing so is greater than that from the outside options. Wages can be determined endogenously in this type of models through the firm and the worker bargaining over their respective outside options to split the joint surplus. We demonstrate in Internet Appendix D that the separation decisions solved in our model are consistent with those under a sequential auction bargaining framework, which is widely used to model wage distribution in the literature (e.g., Postel-Vinay and Robin 2002; Cahuc, Postel-Vinay, and Robin 2006; Jarosch 2023). Even though the model can generate predictions on wages, we choose not to match them to the wage data for two reasons. First, banker compensation often contains various components, including base salary, performance bonus, equity incentive, and signing bonus or retention package. High-quality data on total compensation is difficult to find. Second, our granular data allows us to infer the evolution of bankers' human capital directly from their output (deal advising history), which is arguably more accurate than relying on wage data. This is because matching the wage data entails the researchers taking a stand on the wage determination process, such as the relative bargaining power between workers and firms. These factors are unobservable and challenging to identify from the data. Though different bargaining power can lead to wide variations in wage, we show in Internet Appendix D that they generate the same set of real outcomes (including output and separation decision), which represents another advantage of using deal advising history in our identification process.

6. Conclusion

We examine how human capital portability affects the careers of skilled workers in the financial industry. We build and estimate a dynamic model in which bankers accumulate both general and firm-specific human capital through their deal-advising experience. Bankers optimize over the opportunity to accumulate more general human capital in bulge bracket banks and a higher return to human capital offered by boutique banks. Bankers' exploring their fit with employers over time introduces another layer of friction, making this trade-off particularly important for their long-run career outcomes.

Our estimation yields several insights. First, a significant fraction of human capital is not portable even though bankers perform similar tasks across firms. Our study thus differs from prior studies focusing on task-specific human capital. Moreover, human capital portability varies significantly across sectors. The heterogeneity in both industry specialization and within-firm collaboration seems to contribute to such differences. This suggests that firm organizational structure and workplace collaboration can play a key role in determining human capital portability. Finally, bankers exhibit time-varying preferences over the two sectors of banks—novice bankers value human capital portability more and prefer working in bulge bracket banks, while senior bankers put more weight on the return to human capital and prefer boutique banks. Crucially, the high level of firm-specific human capital in boutique banks discourages high-quality bankers from joining them at early career stages, thus hindering the allocation of skilled labor in the economy.

Over the past decades, many industries have accelerated automation and technological adoption, and thus increasingly rely on skilled workers to perform nonroutine tasks. Firms have also evolved to differentiate to a greater extent in terms of their organizational structures and the scope of their services. In this environment, workers often need to develop specialized knowledge, manage and collaborate with other individuals in their firms, and establish relationships with a small set of clients, all of which lead to the buildup of firm-specific human capital. Implications from our study are particularly relevant for understanding workers' career choices as well as the allocation of human capital in the modern U.S. economy.

Code Availability: The replication code and data are available in the Harvard Dataverse at https://doi.org/10.7910/DVN/WJKM5L.

References

Acemoglu, D., and J.-S. Pischke. 1998. Why do firms train? Theory and evidence. *Quarterly Journal of Economics* 113:79–119.

———. 1999. The structure of wages and investment in general training. *Journal of Political Economy* 107: 539–72.

Akkus, O., J. A. Cookson, and A. Hortaçsu. 2016. The determinants of bank mergers: A revealed preference analysis. *Management Science* 62:2241–58.

———. 2021. Assortative matching and reputation in the market for first issues. *Management Science* 67: 2049–74.

Albuquerque, R., and E. Schroth. 2010. Quantifying private benefits of control from a structural model of block trades. *Journal of Financial Economics* 96:33–55.

———. 2015. The value of control and the costs of illiquidity. *Journal of Finance* 70:1405–55.

Almeida, R., and P. Carneiro. 2009. The return to firm investments in human capital. *Labour Economics* 16: 97–106.

Baghai, R., R. Silva, and L. Ye. 2019. Teams and bankruptcy. *Research Paper, Swedish House of Finance.* .

Bartel, A. P., N. D. Beaulieu, C. S. Phibbs, and P. W. Stone. 2014. Human capital and productivity in a team environment: Evidence from the healthcare sector. *American Economic Journal: Applied Economics* 6:231–59.

Becker, G. S. 1962. Investment in human capital: A theoretical analysis. *Journal of Political Economy* 70:9–49.

Berk, J. B., R. Stanton, and J. Zechner. 2010. Human capital, bankruptcy, and capital structure. *Journal of Finance* 65:891–926.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin. 2006. Wage bargaining with on-the-job search: Theory and evidence. *Econometrica* 74:323–64.

Chen, J., H. Hong, M. Huang, and J. D. Kubik. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* 94:1276–302.

Cohn, J. B., Z. Liu, and M. I. Wardlaw. 2022. Count (and count-like) data in finance. *Journal of Financial Economics* 146:529–51.

Deuskar, P., J. M. Pollet, Z. J. Wang, and L. Zheng. 2011. The good or the bad? Which mutual fund managers join hedge funds? *Review of Financial Studies* 24:3008–24.

Diamond, P. A. 1982. Wage determination and efficiency in search equilibrium. *Review of Economic Studies* 49:217–27.

Eberly, J., and N. Wang. 2009. Capital reallocation and growth. *American Economic Review* 99:560–6.

Egan, M., G. Matvos, and A. Seru. 2019. The market for financial adviser misconduct. *Journal of Political Economy* 127:233–95.

Ellul, A., M. Pagano, and A. Scognamiglio. 2020. Career risk and market discipline in asset management. *Review of Financial Studies* 33:783–828.

———. 2021. Careers in finance. *Working Paper, Center for Financial Studies* .

Flinn, C. J. 1986. Wages and job mobility of young workers. *Journal of Political Economy* 94:S88–S110.

Fredriksson, P., L. Hensvik, and O. N. Skans. 2018. Mismatch of talent: Evidence on match quality, entry wages, and job mobility. *American Economic Review* 108:3303–38.

Gao, J., K. Kleiner, and J. Pacelli. 2020. Credit and punishment: Are corporate bankers disciplined for risk-taking? *Review of Financial Studies* 33:5706–49.

Gathmann, C., and U. Schönberg. 2010. How general is human capital? A task-based approach. *Journal of Labor Economics* 28:1–49.

Gorbenko, A. S., and A. Malenko. 2014. Strategic and financial bidders in takeover auctions. *Journal of Finance* 69:2513–55.

Groysberg, B., L.-E. Lee, and A. Nanda. 2008. Can they take it with them? The portability of star knowledge workers' performance. *Management Science* 54:1213–30.

Herkenhoff, K., J. Lise, G. Menzio, and G. M. Phillips. 2018. Production and learning in teams.

Huckman, R. S., and G. P. Pisano. 2006. The firm specificity of individual performance: Evidence from cardiac surgery. *Management Science* 52:473–88.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan. 1993. Earnings losses of displaced workers. *American Economic Review* 83:685–709.

Jaggia, P. B., and A. V. Thakor. 1994. Firm-specific human capital and optimal capital structure. *International Economic Review* 35:283–308.

Jarosch, G. 2023. Searching for job security and the consequences of job loss. *Econometrica* 91:903–42.

Jovanovic, B. 1979. Job matching and the theory of turnover. *Journal of Political Economy* 87:972–90.

Jovanovic, B., and P. L. Rousseau. 2002. The Q-theory of mergers. *American Economic Review* 92:198–204.

Landau, P. 2016. Investment banks' employment contracts—What to watch for. https://news.efinancialcareers.com/uk-en/238669/employment-contracts-investment-banks.

Lanteri, A. 2018. The market for used capital: Endogenous irreversibility and reallocation over the business cycle. *American Economic Review* 108:2383–419.

Lazear, E. P. 2009. Firm-specific human capital: A skill-weights approach. *Journal of Political Economy* 117:914–40.

Lazear, E. P., and K. L. Shaw. 2007. Personnel economics: The economist's view of human resources. *Journal of Economic Perspectives* 21:91–114.

Lee, D., and K. I. Wolpin. 2006. Intersectoral labor mobility and the growth of the service sector. *Econometrica* 74:1–46.

Levine, O. 2017. Acquiring growth. *Journal of Financial Economics* 126:300–319.

Li, S., and T. M. Whited. 2015. Capital reallocation and adverse selection.

Lynch, A. W., and J. A. Wachter. 2013. Using samples of unequal length in generalized method of moments estimation. *Journal of Financial and Quantitative Analysis* 48:277–307.

Mackenzie, N. 2023. Biggest hedge funds will keep lion's share of customers in 2023, data shows. https://www.reuters.com/business/finance/biggest-hedge-funds-will-keep-lions-share-customers-2023-data-shows-2023-01-05/.

Maksimovic, V., and G. Phillips. 2001. The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56:2019–65.

Marx, M., D. Strumsky, and L. Fleming. 2009. Mobility, skills, and the michigan non-compete experiment. *Management Science* 55:875–89.

Morrison, A. D., and W. J. Wilhelm. 2007. *Investment banking: Institutions, politics, and law*, vol. 10. Oxford, UK: Oxford University Press.

Mortensen, D. T. 1982. Property rights and efficiency in mating, racing, and related games. *American Economic Review* 72:968–79.

Moscarini, G. 2005. Job matching and the wage distribution. *Econometrica* 73:481–516.

Nagypál, É. 2007. Learning by doing vs. learning about match quality: Can we tell them apart? *Review of Economic Studies* 74:537–66.

Naidu, S., E. A. Posner, and G. Weyl. 2018. Antitrust remedies for labor market power. *Harvard Law Review* 132:536–601.

Parsons, D. O. 1972. Specific human capital: An application to quit rates and layoff rates. *Journal of Political Economy* 80:1120–43.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2015. Scale and skill in active management. *Journal of Financial Economics* 116:23–45.

Pastor, L., R. F. Stambaugh, L. A. Taylor, and M. Zhu. 2021. Diseconomies of scale in active management: Robust evidence. Discussion Paper, CEPR.

Peters, A. 2019. What ruling on noncompete clauses means for banks—and job hunters. https://www.americanbanker.com/news/what-ruling-on-noncompete-clauses-means-for-banks-and-job-hunters.

Polanyi, M. 1966. The logic of tacit inference. *Philosophy* 41:1–18.

Postel-Vinay, F., and J.-M. Robin. 2002. The distribution of earnings in an equilibrium search model with state-dependent offers and counteroffers. *International Economic Review* 43:989–1016.

Silva, J. S., and S. Tenreyro. 2011. Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters* 112:220–2.

Sun, Q., and M. Z. Xiaolan. 2019. Financing intangible capital. *Journal of Financial Economics* 133:564–88.

Topel, R. 1991. Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy* 99:145–76.

Travillian, A. 2022. Top 5 fund families. https://www.investopedia.com/articles/investing/010616/look-barrons-top-5-mutual-fund-families.asp.

Warusawitharana, M. 2008. Corporate asset purchases and sales: Theory and evidence. *Journal of Financial Economics* 87:471–97.

Wasmer, E. 2006. General versus specific skills in labor markets with search frictions and firing costs. *American Economic Review* 96:811–31.

Yang, L. 2008. The real determinants of asset sales. *Journal of Finance* 63:2231–62.

Zhu, M. 2018. Informative fund size, managerial skill, and investor rationality. *Journal of Financial Economics* 130:114–34.

Zingales, L. 2000. In search of new foundations. *Journal of Finance* 55:1623–53.