# Human Capital Portability and Careers of M&A Advisors

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**Abstract**

We estimate the importance of firm-specific human capital in explaining skilled workers' choices between working for large, diversified firms and small, focused firms. We develop a model that allows workers to accumulate both general and firm-specific human capital through their work experience and learn about their match quality with current employers over time. In this framework, workers' choices are shaped by trading-off the efficiency gain from working for more focused firms against the high level of firm-specific human capital they expect to acquire in such firms. The model is estimated to match granular data on M&A advisors' career trajectories in bulge bracket (diversified) and boutique (focused) banks. Our estimation suggests that 44% of human capital accumulated in boutique banks is firm-specific and hence not portable, while the fraction is only 12% in bulge bracket banks. Such a difference explains why bankers are more likely to choose bulge bracket banks at the start of their careers but increasingly migrate to boutique banks when they become more seasoned. Overall, human capital (non-)portability hinders labor reallocation, and it significantly influences the composition of banks in the M&A advisory industry.

**Key words:** labor mobility, human capital portability, career path, M&A advisor

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# Introduction

Labor mobility shapes firm boundaries and fosters innovation and growth (Zingales (2000); Marx et al. (2009); Berk et al. (2010)). In industries and occupations requiring highly skilled workers, labor mobility critically depends on the presence of firm-specific human capital (Becker (1962); Parsons (1972); Lazear (2009); Custódio et al. (2013)).[1] Firm-specific human capital involves tacit knowledge regarding the organization, familiarity with procedures, and relationships with coworkers and clients, etc. This type of knowledge is "non-portable" because it cannot be applied to other firms and is lost when employees switch jobs. As workers accumulate firm-specific skills, they become more productive in the current employers, but face greater costs in job transitions and more setbacks when they regain employment.

Existing studies generate directional predictions regarding how specific skills affect labor market conditions. Yet, they do not quantify the buildup of firm-specific human capital or its effects on workers.[2] We thus have limited ability to answer important questions such as: How much firm-specific human capital is acquired by workers in skill-intensive industries? How quickly does it grow with experience? To what extent does the portability of human capital vary across firms and shape workers' career path? We answer these questions by estimating a dynamic model, which endogenizes workers' career choices and the portability of their human capital. The model also embeds realistic features such as learning by doing and learning about the match quality between employer and employees. Our structural approach allows us to track the accumulation and depreciation of both specific and general human capital. Consequently, it allows us to gauge the portability of workers' human capital and how it varies across different types of firms.

We estimate model parameters to match granular data on investment bankers' career paths in the M&A advisory industry. By doing so, we quantify the portability of human capital and

[1]Prior studies such as Topel (1991), Connolly and Gottschalk (2006), and Brown and Matsa (2016) show that more experienced, highly educated, and highly skilled workers bear higher unemployment costs because their jobs require more firm-specific investment by the employee.

[2]Gathmann and Schönberg (2010) measure task-specific human capital based on surveys of task usage. Poletaev and Robinson (2008) construct skill-specificity measures based on industry-level skill descriptions. Deming and Kahn (2018) examine the difference in job skill descriptions across firms. Neither study quantify the proportion of worker skills that are firm specific.

show that a significant portion of worker human capital is firm specific (i.e., non-portable). Portability is significantly lower for workers in small, focused firms than for workers in large, diversified firms. Facing job opportunities from both types of firms, workers' decisions are largely driven by the tradeoff between the high efficiency of focused firms and the low portability of the skills they expect to develop in those firms. The model also shows that the non-portability of human capital can aggravate other labor market frictions, such as unobservable match quality, and impede the efficient allocation of skilled labor in the industry.

Using the M&A advisory industry as a setting offers several advantages. First, human capital represents a major, if not the only, productive input for M&A advisory firms. This is because the main tasks of M&A advisors are to acquire information, provide guidance, and intermediate between bidders and targets, all of which require human touch and relationship-building. Second, banker output can be observed at the individual level by the deal volume they advised in the past. Third, bankers accumulate knowledge and skills during the deal-making process (i.e., learning-by-doing), some of which are firm-specific, embedded in bankers' relationships with team members and clients. Finally, advisory firms in this industry provide similar business services, so that firm-specific human capital is not confounded by task-specific skills.

Like many other business service industries, such as consulting and law, the M&A advisory industry is populated by two types of firms (banks): bulge bracket banks and boutique banks. Bulge bracket banks are large, diversified firms, which offer a full range of investment banking products and serve a broad client base. In contrast, boutique banks are small and focused on advising M&A deals. They advocate individual attention to a select group of clients. The different business models suggest that the specificity of human capital may vary across the two sectors, potentially being higher in the boutique sector. In the meanwhile, boutique banks bear lower overhead costs and can distribute more profit to their bankers. They are thus considered to have more efficient operations.[3]

[3]Anecdotal evidence suggests that in boutique firms, workers can build up specialized skills and receive a larger share of the deal profit. See, for example, https://www.wallstreetoasis.com/salary/investment-banking-compensation. The career benefits and specialization of boutique firms are often discussed at career forums and industry journals. See, for example, Stott (2017) and DeChesare (2020). The high efficiency and profitability of

These features of the M&A advisory industry are reflected in our model setup. The model contains two sectors, diversified (bulge bracket) and focused (boutique) sectors, with homogeneous firms in each sector. The goal of all firms is to generate deals. Workers can acquire both general and firm-specific human capital through their work experience (Nagypál (2007)). We refer to the proportion of firm-specific human capital a banker gains through each deal as "portability." The model allows portability and efficiency to vary across sectors.[4]

In each sector, productivity is determined by a banker's human capital and by the match quality between the banker and the employer. A high match quality means that the banker has a strong synergy with the employer and can generate more deals. The banker does not observe match quality but can learn about it over time based on past deal volume (Jovanovic (1979)). In each period, the banker faces the following career choices: staying with the current employer, switching to another employer in the same sector, or switching to the opposite sector. Perceived match quality and portability jointly determine job separation — the banker is more likely to leave the current employer if he learns that his match quality is low. Yet, his incentive to switch jobs is counter-balanced by the potential loss of firm-specific human capital during the transition. When choosing between the two sectors, the banker accounts for the differences in both efficiency and human capital portability across the two sectors.

To compare model predictions with actual empirical patterns, we gather data on investment bankers' employment history and the M&A deals they advise. Data regarding bankers' deal-advising history come from MergerMarket, a platform that collects the names of the investment bankers advising each merger deal and their employment affiliations. For each banker in our sample, we compile his complete career paths using the BrokerCheck Report prepared by the Financial Industry Regulatory Authority (FINRA). All individuals involved in security-dealing are required to register with FINRA and disclose their employment history. Combining information from these sources, we assemble a large sample of investment bankers' career trajectories.

boutique firms also separates us from discussions on the relation between financially constrained firms and human capital investment (Becker (1962), Popov 2014).

[4] The model imposes no priors on the portability and efficiency across the two sectors, and we let the data guide our estimation of these values.

The sample spans the period of 2001 through 2018, covering 4,318 bankers working for over 100 M&A advisory firms. This granular dataset allows us to gauge a banker's human capital buildup and his career choice at each point of time.

Matching moments generated by the model to those in the data, we are able to estimate and quantify several important parameters, including the portability of human capital generated in both sectors, the cross-sectional distribution of match quality, and the efficiency of different types of banks. The key empirical pattern that helps us identify human capital portability across the two sectors is the change in banker performance around job transitions. Given that firm-specific human capital is lost in job transition, the performance decline following job transitions is informative of the (non-)portability of human capital possessed by workers working in a firm. Yet empirically, the observed performance change is confounded by an endogenous selection effect: bankers with poor perceived match quality are more likely to depart and their expected match quality with the new employer improves subsequently. Our approach allows us to tease out the selection effect and gauge the loss of human capital during job transitions.

We document that bankers on average experience a decline in performance around job changes, but bankers departing boutique firms experience a stronger and more persistent decline in than those departing bulge bracket firms. This striking data feature guides our model to identify the differences in human capital portability across two sectors: in a bulge bracket firm, around 85% of human capital accumulated is portable while in a boutique firm, this fraction is only 60%. Despite of the low portability in human capital build-up, boutique firms exhibit higher efficiency than their bulge bracket counterparts. The estimated efficiency difference is around 3%, suggesting that, given the same level of human capital, boutique firms generate 3% higher profit after administrative and regulatory costs. On the other hand, positions in boutique firms also offer less stable income stream, less prestige, but more private benefit as the individuals are more likely to have greater decision-making authority. Our efficiency parameter should be interpreted as a net benefit after adjusting the effects of these factors.

Our estimates also help uncover and explain novel patterns in the labor market for M&A advisors. First, bankers are less likely to leave boutique firms than to leave bulge bracket firms, because the former provide less portable human capital, making job separation costlier. Consistently, boutique firm employees are willing to tolerate worse match quality, as evidenced by more severe under-performance before job separation. Second, bankers' preference between bulge bracket and boutique firms changes over their career stages. Novice bankers prefer bulge bracket banks because they value generalizable skills and hope to retain the flexibility of relocating to other firms in the future. As bankers become more seasoned, they increasingly migrate to boutique banks in seek of higher returns to their human capital. This pattern suggests that bulge bracket firms act as an "incubator" of human capital, where employees can acquire general knowledge and skills that prove to be valuable for their future careers.

Using the estimated model as a laboratory, we examine the effect of human capital non-portability and its interactions with other labor market frictions. To this end, we consider three counterfactual scenarios: (1) perfect portability, where workers only accumulate general human capital; (2) perfect information, where match quality is revealed immediately to workers upon the start of their employment; and (3) both perfect portability and perfect information. We find that mobility is delayed and productivity growth becomes sluggish when human capital non-probability and imperfect information are both present, highlighting the interaction of these market frictions in shaping labor market conditions and worker output.

We also document novel interactions between human capital non-portability and workers' early career experience. Having good luck in ones' early career accelerates his human capital buildup and increases his ability to generate profit. However, luck can negatively affect the worker later in his career if he is initially matched to the "wrong" employer --- the "lucky" worker mistakenly perceives the initial employer as a good match and stays with the employer for a prolonged period. By the time such misperception is corrected, he has accumulated too much non-portable human capital and finds job transition highly costly. Thus, luck can generate an "reversal effect" in his later career stages: In those stages, the worker is more likely to quit, suffers a greater decline in human capital and productivity, and becomes less attractive in the job market than the average worker.

Finally, we show that human capital portability influences industry structure. We simulate bankers' job migration across the bulge bracket and boutique sectors as we change the gap in human capital portability across the two sectors (the portability in bulge bracket minus the portability in boutique banks). The resulting market share of the boutique sector varies substantially according to these changes. In the data, the market share of boutique banks has increased form 10% in early 2000 to 48% lately, and the pattern is closely matched in our baseline model where the human capital portability gap between the bulge bracket and boutique sector equals 22%. If we counterfactually decrease the human capital portability gap by 50%, the boutique banks would have captured 81% of the market share, whereas if we increase the gap by 50%, there will hardly be any increase in the boutique banks' market shares over the past two decades. The variation of human capital portability across firms hence plays a pivotal role in defining firm boundary and shaping industry structure.

In closing, we provide two caveats regarding our results. First, our model abstracts from discussing wages or compensation contracts by assuming that a banker and a firm will stay matched as long as doing so generates positive joint surplus. With frictionless bargaining, the outcome is that the two parties split the surplus they create in a way that the banker is compensated on par with his outside option at any time plus a share of the surplus. Therefore, the banker's optimal career decisions will be the ones that maximize the joint surplus. Our setting is also consistent with an alternative environment where there is no bargaining and all banks simply impose a compensation structure that offers bankers a given share of their revenue. In this case, the banker's career decisions will serve to maximize his expected lifetime revenue from deal generating, which can be shown to also yield the maximal joint surplus. Second, we note that while we match the model to empirical patterns in the M&A advisory industry, the model's predictions regarding worker career choices can be extended to other industries that rely heavily on skilled labor and contain heterogenous firms in terms of portability and efficiency.

This study contributes to two strands of literature. First, we add to the literature on firm-specific skills and human capital mobility. Seminal work in labor economics shows that the portability of human capital is an important determinant of many labor market outcomes, including workers' job participation and separation, wages, and firms' incentive to provide training (see, e.g., Becker (1962), Jovanovic (1979), Jacobson et al. (1993), and Acemoglu and Pischke (1999)). It has also been shown to influence long-term economic growth (Ljungqvist and Sargent (1998)). Recent discussions on the portability of human capital focus on certain specific tasks or industries, such as CEOs, surgeons, and security analysts. Our study contributes to this line of research by quantifying the level of firm-specific human capital acquired by workers in skill-intensive industries. In addition, our findings suggest that workers in diversified firms obtain more general knowledge, while those in small, focused firms gain more firm-specific skills. Our structural approach allows us to compare the portability of human capital that workers generate from each type of firms, which represents an innovation to the literature.

Our study also contributes to the literature on capital (mis)allocation. Classic q-theory suggests that capital should flow to the most efficient users to achieve its best productivity (Jovanovic and Rousseau (2002)). Existing studies have focused mainly on physical capital allocation and find supportive evidence (Maksimovic and Phillips (2001), Yang (2008), and Warusawitharana (2008)). Other studies document that various frictions, such as investment irreversibility (Bertola and Caballero (1994), Lanteri (2018)), and the information asymmetry on the used capital market can generate significant distortion on the flow of capital (Li and Whited (2015)). We complement the prior literature by studying the reallocation of highly skilled human capital. We document that the lack of portability in firm-specific knowledge presents a main friction that distorts the flow of human capital. We also use micro-level data to gauge the extent to which the non-portability of human capital influences employee productivity and the composition of the M&A advisory industry.

# 1 Model

## 1.1 Model setup

We model a continuum of infinitely lived investment bankers, ex ante identical, of measure one. An investment banker has to join a bank in order to perform M&A advisory service (that is, to produce). There are two types of advisory banks in the economy – bulge bracket banks and boutique banks. We introduce their differences as we present the model in detail below. The main goal of our model is to characterize individual bankers' career choices and to examine the efficiency of labor allocation across the two advisory sectors.

Each job is modeled as a pair of an individual $i$ and a bank $b$. As in previous studies (see e.g., Jovanovic (1979) and 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 culture of the bank. We assume that $\mu_{i,b}$ is drawn upon a pair is formed and it remains unchanged until the pair breaks up. As the individual switches to a new employer $b'$, a new match quality is drawn. We assume that match quality is i.i.d. across pairs, and follows a common Bernoulli distribution: the match quality is high with probability $q$ and is low with probability $1-q$, that is, $P\{\mu = 1\} = 1 - P\{\mu = 0\} = q$. The distribution is common knowledge, but the realization of $\mu_{i,b}$ is *unobservable* to any agents 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 more 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 non-portable human capital. Portable human capital captures a banker's generalizable skills such as codified, analytical skills, ways to acquire information, networks with other bankers in the industry, etc. It can be carried over to a new employer with the banker following a job switch. Non-portable human capital is employer-specific, including the relationships with colleagues and clients of the current employer, and the ability to work with the organization structure and resources of the current employer. Non-portable human capital evaporates once the banker switches to a new employer (see e.g., Topel (1991)). We denote the portable human capital as $h$ and the non-portable human capital as $\omega$.

Labor is the only input to production. Production output is the number of deals completed by a banker-bank pair. This is because M&A advisors are largely compensated for advising and completing deals, and the deal advisory process requires significant human interaction and influence.[5] Each period $t$, a banker $i$ who works for bank $b$ advises $n_{i,b,t}$ deals. We assume that the deal number $n_{i,b,t}$ is stochastic and follows a Poisson distribution:

$$P\{n_{i,b,t} = N\} = \frac{(m_{i,b,t})^N}{N!} e^{-m_{i,b,t}} \tag{1}$$

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

$$m_{i,b,t} = (a \cdot \mu_{i,b} + c) \cdot (h_{i,t} + \omega_{i,t}) + b \tag{2}$$

In other words, banker output is determined by three factors: the match quality between the banker and his employer, portable human capital, and non-portable human capital.

Profits from deal advising are proportional to the deal number:

$$\pi_{i,b,t} = \lambda_s \cdot n_{i,b,t} \tag{3}$$

where $s$ denotes the sector, with $s = 0$ indicating bulge bracket banks and $s = 1$ indicating boutique banks; $\lambda_s$ captures sector-specific efficiency: when $\lambda_s$ is large, the M&A advisor creates more value for its clients and receives higher compensation. The compensation is split between the investment banker and the advisory firm.

[5] While investment advisors may charge a flat retainer fee that does not depend on deal outcomes, the fee amount is much lower than the commission for successful deals.

A banker builds up human capital by advising deals (i.e., learning-by-doing). Without considering a job switch, banker human capital evolves following the law of motion below:

$$\omega_{i,t+1} = \rho \cdot \omega_{i,t} + \delta_s \cdot \ell(\omega_{i,t}) \cdot n_{i,b,t} \tag{4}$$

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

where $1-\rho$ controls the fraction of old human capital that becomes obsolete and $\ell(\cdot)$ determines the speed of learning-by-doing.[6] The parameter $\delta_s \in [0,1]$ indicates the proportion of human capital acquired through each deal that is firm-specific: when $\delta_s$ is high, a larger fraction of human capital accumulates to its non-portable component. $\delta_s$ varies across sectors.

Overall, there are two key parameters differentiating between the bulge bracket and boutique sectors: efficiency ($\lambda_s$) and human capital specificity ($\delta_s$). Bankers working for boutique firms may accumulate firm-specific human capital at a different speed from bankers working for bulge bracket firms. Boutique bank employees and bulge bracket bank employees also derive different levels of surplus from their work. We allow both parameters to vary across the two bank sectors, but require them to be the same for all banks in the same sector $s$.

The last key element of our model is the perceived match quality. Although the true match quality is unobservable to any agents in the model, bankers can learn about it by observing the realized deal volume $n_{i,b,t}$. As Equation 1 suggests, $n_{i,b,t}$ serves as a signal of deal arrival rate, $m_{i,b,t}$, which is in turn correlated with match quality $\mu_{i,b}$. At the beginning of each period $t$, the banker perceives that his employer is a high-quality match with probability $p_{i,b,t}$. Upon the realization of deal volume in this period, he updates his perception to $p_{i,b,t+1}$ based on the

[6] If $\ell(x)$ is a postive constant, then human capital builds up 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 of "low-hanging fruit gets picked first."

Bayes' law:

$$
\begin{aligned}
p_{i,b,t+1} &= P\{\mu_{i,b} = 1 | n_{i,b,t} = N, p_{i,b,t}\} \\
&= \frac{p_{i,b,t-1} \cdot \frac{(m_1)^N}{N!} e^{-m_1}}{p_{i,b,t-1} \cdot \frac{(m_1)^N}{N!} e^{-m_1} + (1 - p_{i,b,t-1}) \cdot \frac{(m_0)^N}{N!} e^{-m_0}}
\end{aligned} \tag{6}
$$

where $m_1$ and $m_0$ is the value of $m_{i,b,t}$ in Equation 2 when $\mu_{i,b} = 1$ and $\mu_{i,b} = 0$, respectively. This learning process suggests that a banker considers his employer more likely to be a good match if he has experienced a higher deal volume in the past.

Based on the above discussion, each banker in our model can be characterized with a vector of state variables, the sector he works in, the general and specific human capital he possesses, and the perceived match quality with his current employer, $(s, h, \omega, p)$.

### 1.2 Bellman equations

We now derive the Bellman equation for bankers' career choices. The model timeline flows as the following: at the beginning of each period, a banker chooses between staying with the current employer or switching to a new bank before production takes place. Though 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 after working for the current employer.[7] The banker's perceived match quality with the new employer follows a common prior $P\{\mu = 1\} = q$. Lastly, at the end of each period, there is an exogenous probability $\eta$ 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 next period, and the Bellman equation below characterizes the value function for a pair of an investment banker and

[7] This assumption is consistent with the fact that many bankers switch jobs after they get their year-end bonus from the current employers even though they have decided earlier in the year that they would leave.

his current employer:

$$U(s,h,\omega,p) = \pi + \beta \cdot (1-\eta) \cdot E\left[U(s,h^{'},\omega^{'},p^{'})\right] \\ + \beta \cdot (1-\eta) \cdot max\left\{0, \chi\Sigma_1(s,h,\omega,p), \chi\Sigma_2(s,h,\omega,p)\right\} \tag{7}$$

where

$$\Sigma_1(b,h,\omega,p) = E\left[U(s,h^{'},0,q)\right] - E\left[U(s,h^{'},\omega^{'},p^{'})\right] \tag{8}$$

$$\Sigma_2(b,h,\omega,p) = E\left[U(1-s,h^{'},0,q)\right] - E\left[U(s,h^{'},\omega^{'},p^{'})\right] \tag{9}$$

The first term on the right-hand-side of Equation 7 is the new profit generated this period, which is shared by the banker and the bank. The second term is the continuation value as 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. We specify the surplus following Jarosch (2015) in which the worker gets a fraction of $\chi$ of the total surplus when he is paired with a new employer. We provide detailed derivation in the Appendix. Equation 8 captures the expected surplus from switching to a new bank in the current sector (and thus $s$ remains the same), and Equation 9 captures the expected surplus from switching to a new bank in the other sector (and thus $s$ becomes $1-s$). Only portable human capital, $h$, is carried over to the new employer, and non-portable human capital, $\omega$, is lost during the job switch. Upon job switch, the banker's perceived match quality with the new employer resets to the prior distribution.

Our paper does not explicitly model how profit is split between the banker and the bank, and thus it is silent on optimal contracting. We study the accumulation of match-specific capital in the framework introduced by Diamond (1982) and Mortensen (1982). In this framework, separation is bilaterally efficient: It takes place only when the joint surplus of the match falls below that of an alternative match. This separation decision is consistent with a Nash bargaining framework that can help pin down the wage, as shown in Moscarini (2005).

### 1.3 Model mechanism

As discussed in Section 1.1, the two sectors (bulge bracket and boutique) differ in two dimensions: efficiency, captured by the parameter $\lambda_s$, and human capital portability, captured by the parameter $1-\delta_s$. Bankers value efficiency and human capital portability differently in different stages of their career, so the tradeoff between efficiency and portability determines the sorting of bankers into the two sectors. We present the full model solution in Section 1.4. In this section, we present and solve a simplified version, which captures the main tradeoff in the full model with the help of additional assumptions. With this simplified model, we are able to present an analytical solution and demonstrate the economic mechanisms more clearly.

In the simplified version, we model the career choice of a departing banker between joining a bulge bracket firm and a boutique firm. The departing banker has portable human capital $h$, and the non-portable human capital $\omega$. We make the following additional assumptions to facilitate our analysis in the simplified model:

1. The match quality $\mu$ will be perfectly revealed one period after the banker joins a firm;
2. The number of deals the banker advises is deterministic, as in Equation 2;
3. If the match quality is good, the banker stays with the firm forever; if the match quality is bad, the banker switches to a new firm in the same sector and redraws the match quality.

Assumption 1 features the simplest setting of stochastic match quality, with all uncertainty being resolved after one period. This assumption retains the banker's incentive to relocate upon a bad match but simplifies his learning process. Recall that we assume the deal number to follow a Poisson process in the full model, which prevents the match quality from being fully revealed. Yet, given that the learning process is degenerated in the simplified model, there is no need to retain randomness in the deal number process. Assumption 2 thus makes the deal number process deterministic. Assumption 3 allows a banker to pick the sector only once (in the initial period), and it rules out the banker's dynamic choices of sectors along his career path. Despite that, we can analyze how a banker's choice of sectors varies with his existing human capital by examining the comparative statics of the model solution with respect to $h$.

Let $V_s(h)$ denote the value function of a banker in sector $s$, and we set $\ell(h) = \ell(\omega) = \ell$ in Equations 4-5 and $c = 0$ in Equation 2 to facilitate our analysis in the simplified model. Now consider two possible scenarios in the next period as the match quality is revealed. We provide a detailed derivation of the results presented below in Appendix A.

If the match quality is good, then the banker stays with the same bank forever, and the continuation value is:

$$\begin{aligned} U_s &= \sum_{t=1}^{\infty} \beta^{t-1} \lambda_s \left(a \cdot (h_{t+1} + \omega_{t+1}) + b\right) \\ &= \lambda_s \left[ \frac{\left(a\overline{h} + b\right)}{1-\beta} + \frac{a\left((\rho + a\ell) \cdot h + b\ell - \overline{h}\right)}{1 - \beta\left(\rho + a\ell\right)} \right] \end{aligned} \tag{10}$$

where $\overline{h} = \frac{b\ell}{1-(\rho + a\ell)}$ is a constant.

If the match quality is low, the banker switches to a new bank in the same sector and draws a new match quality. He then faces the same situation as in the first period except that his portable human capital becomes $\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b$ and non-portable human capital resets to zero. His continuation value, therefore, is equal to $V_s\left(\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b\right)$.

Combining the two possible situation, we can write down the Bellman equation as

$$V_s(h) = \lambda_s \left(a \cdot q \cdot h + b\right) + \beta \left[q \cdot U_s + (1-q) V_s\left(\rho \cdot h + (1-\delta_s) \cdot \ell \cdot b\right)\right]$$

Solving for $V_s(h)$ with Taylor expansion yields:

$$V_s(h) \approx \lambda_s \left(A_0 + A_1(1 - \delta_s) + A_2 h\right) \tag{11}$$

where the coefficient $A_0$ to $A_2$ are all positive, as defined in Equations A.8 through A.10 in Appendix A.

Equation 11 suggests that $\frac{dV_s(h)}{d\lambda_s} > 0$ and $\frac{dV_s(h)}{d(1-\delta_s)} > 0$ and thus the value function increases with both efficiency $\lambda_s$ and portability $1-\delta_s$. If each of the two sectors (bulge bracket v.s. boutique) has an advantage in only one dimension, a banker need to trade-off between these efficiency and portability when choosing which sector to join. Ultimately, the banker's choice depends on the value function. For example, he chooses the bulge bracket sector ($s = 0$) if $V_0(h) > V_1(h)$.

Critically, a banker's career choice also depends on the level of his existing human capital. Note that Equation 11 suggests that $\frac{d^2V_s(h)}{d\lambda_s dh} > 0$ and $\frac{d^2V_s(h)}{d(1-\delta_s)dh} = 0$, so the marginal value of $\lambda_s$ increases with $h$. In other words, efficiency and human capital are complementary. This is because high efficiency increases the gains from each deal and skilled bankers advise more deals. On the other hand, the marginal benefits of portability, $1 - \delta_s$, does not grow with human capital. The simplified model therefore predicts that as a banker gains more human capital, he weighs more on efficiency than on portability, and this preference leads more skilled (experienced) banker to join the more efficient sector.

While the simplified model helps demonstrate the tradeoff between efficiency and portability as the main mechanism, it requires a few restrictive assumptions. For example, it rules out the learning about match quality and precludes a banker from switching sectors as his human capital grows. We solve the full model next and illustrate the model solution.

## 1.4 Model Solution

To solve the full model, we return to the setting laid out in Sections 1.1 and 1.2. We specify the function $\ell(\cdot)$ in Equations 4 and 5 as

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

If $\alpha > 0$, it features a declining marginal benefits of learning-by-doing as a banker's human capital grows, a standard assumption maintained in many learning models. Meanwhile, if $\alpha = 0$, it nests the constant marginal benefits of learning-by-doing as we assumed in the simplified model. We solve the value function and the associated optimal career choice using numerical methods. Next, we illustrate how a banker's career choice varies with his human capital, the perceived match quality, and the current sector he works in. To do so, we set the model parameters to their estimated values and simulate the model to construct a panel of bankers who follow the optimal career choices in the estimated model.[8] To illustrate the mechanism, we focus on bankers who have not switched jobs previously, so that their portable human capital $h$, and non-portable human capital, $\omega$, have been accumulating at the same speed.

Figure 1 shows how labor mobility varies with the level of human capital and the perceived match quality. We define labor mobility as the 5-year cumulative probability of job transition for individual bankers. Panel A presents the results for bankers who are currently employed in the bulge bracket sector and Panel B presents the results for bankers in the 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. Labor mobility is shown by the color scale, with lighter colors indicating higher mobility.

Both panels suggest that job separation rate decreases with perceived match quality and established human capital. The effect of perceived match quality is well expected, because a lower match quality predicts lower deal volume, which in turn reduces surplus and depresses human capital accumulation. Bankers follow a threshold decision rule, swtiching jobs as soon as the perceived match quality drops below a cutoff. The cutoff value, however, differs acorss bankers and depends critically on their human capital. Given that firm-specific human capital is lost upon job switch, bankers that have accumulated more specific human capital require a lower cutoff value to move.

There is, however, a striking difference between bankers employed in the two sectors. Holding fixed banker characteristics (human capital and perceived match quality), bankers in bulge bracket firms (Panel A) are much more likely to switch jobs than those employed in boutique firms (Panel B). This is related to the composition of general vs. firm-specific human capital

[8] Parameter estimates are reported in Table 3, and we defer the discussion of them to the next section.

of these bankers. Our estimates in Section 2 suggest that bankers build up a larger fraction of non-portable human capital when they work in the boutique sector, and thus lose more of their human capital during job transition. These bankers are willing to tolerate lower match quality to avoid costly job transition.

Next, we analyze the value of portable and non-portable human capital in the model. We measure the marginal value of portable and non-portable human capital as $\frac{dU}{dh}$ and $\frac{dU}{d\omega}$, with $U$ being the value function solved in Equation 7. Since non-portable 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 non-portable human capital relative to the value of portable human capital:

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

Figure 2 illustrates how portability premium varies with match quality and banker human capital using heat maps. We again plot the results for the bulge bracket sector in Panel A and the boutique sector in Panel B. Lighter color in the heat maps means a higher premium for portable human capital.

Intuitively, portability premium should decrease with expected job span. In the extreme case that bankers never expect to leave their employers, there is no distinction between portable and non-portable human capital. As a result, portability premium decreases with both perceived match quality and the established level of human capital, because both indicate job stability. Holding fixed match quality and human capital levels, bankers in bulge bracket firms attach a higher value to general human capital, while boutique bankers derive a greater value from firm-specific human capital. This is because the latter changes jobs less frequently and expects a lower loss from job transitions. Overall, specific human capital is more valuable to bankers with high human capital and bankers employed in the boutique sector.

Last, we examine bankers' choice between the two sectors, which answers the question of "who works for whom." As discussed above, bankers choose between the sectors by trading off the efficiency gain from working for boutique firms against the high level of firm-specific human capital they expect to accumulate in those firms. As bankers accumulate more human capital over time, their choice vary along their career paths. To illustrate this point, 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 3 shows the model solution. We observe that in the early-career stage, almost all bankers choose to stay in bulge bracket banks. Specifically, in the first 10 years of their career path, only about 15% of bankers switch to the boutique sector. This ratio climbs rapidly to 43% during the second 10-year period and nearly 60% in the third decade. Overall, senior bankers have a stronger preference for boutique banks. This is because senior bankers possess a high level of human capital, and the return to human capital plays a dominant role in affecting their career choices. Given that bankers generate higher returns to human capital in boutique banks, their preference towards boutique banks grows with experience. We also observe a similar pattern in the data.

# 2 Estimation

In this section, we describe the sample construction, the simulated method of moments (SMM) estimator, and the intuition behind the estimation method.

## 2.1 Data and Sample Construction

We collect the identity and deal-making history of investment bankers from the MergerMarket database. MergerMarket records M&A deals with transaction value over $5 million conducted during the period of 2000 through 2018 in both U.S. and abroad. It accounts for deals in which the acquirer purchases at least 30% of the equity stake of the target firm. For each deal, Mergermarket provides detailed information on various deal characteristics, including the identities of the acquirer, target, and the M&A advisory bank, the date of the acquisition announcement, the date of deal completion, and the transaction value. The distinguishing feature of the database is that it provides the names of the investment bankers advising the deal and their employment affiliations. This information allows us to estimate bankers' experience, performance, and their human capital accumulation.

For each banker in the sample, we compile his complete career path 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 affiliation 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 definition provided by Wall Street Oasis (WSO), a leading job search forum for the financial services industry. Based on WSO's classification, bulge bracket banks include Goldman Sachs, Bank of America Merill Lynch, Citi, Morgan Stanley, etc. It also classifies 154 investment banks as boutique, including Lazard, Moelis & Co., Centerview, Greenhill, and Perella Weinberg. In our analysis, we exclude bankers' job spans that do not belong to either bulge bracket banks or boutique banks.

Combining information from the above sources, we arrive at a sample of investment bankers' career paths and deal-advising history. The sample spans the period of 2001 through 2018, covering the career trajectory of 4,318 bankers working for 132 M&A advisory firms, among which 14 are bulge bracket banks and 118 are boutique banks.

Bankers' human capital is reflected by the volume of deals they advise. In constructing this measure, we take into account the size of the deals and assume that bankers build more human capital from advising larger deals. Intuitively, advising a $1 billion deal helps a banker gain a stronger reputation in the industry than advising a $10 million deal. It also helps the banker attract more clients in the future. Yet, bankers' human capital may not accumulate in a linear fashion according to deal size. Due to these considerations, we rely on advisory fees as a proxy for human capital attributed to the deal. Fees are designed to compensate advisors for the time and energy they devote to advising a deal. They generally increase with deal size and bankers' expertise. We calculate a fee-adjusted deal number as follows. First, based on information provided by the SDC platinum database, we extrapolate the percentage of fees paid to each deal as a linear function of log deal value. Appendix B shows that the fee percentage-log deal value relation fits closely to a linear function. Based on the fitted relation, we compute a projected fee amount for each deal in our sample. This helps address situations where fee amount is missing in our data.

In the case where a deal is advised by multiple advisors, we split the fees evenly across all bankers. Finally, we assign all deals with below-median advisory fees with a count of one, and count deals with above-median fees according to the ratio of the fees paid to those deals over the median fee. For example, if the median fee is \$5 million, and an acquirer paid 10 bankers a total of \$100 million fees to advise a mega deal, we expect each banker in the mega deal to accumulate twice ($=\frac{100/10}{5}$) as much human capital as the average deal.

### 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 the estimation and explain how they help identify the model parameters.

As an initial step, we calibrate the value of some parameters that we can directly take from prior literature or quantify from the data. Specifically, we set the discount factor $\beta$ to be 0.9, a value commonly used in the literature. We set the exogenous exit rate, $\eta$, to 4% per year, which matches the average dropout rate in the M&A advisory industry. We normalize the efficiency parameter for the bulge bracket sector, $\lambda_0$, to 1. Since value functions are scalable in the model, this normalization does not affect bankers' optimal career choices. Last, note that the function $\ell(\cdot)$ and the expected deal number $m$ jointly determine the speed of human capital accumulation. We cannot identify the parameter $\ell$ in Equation 12 separately from the parameter $a$, $b$, and $c$ in Equation 2. We thus normalize $c$ to be 1 and scale other parameters correspondingly.

We estimate the remaining 9 parameters in an SMM system. These parameters include: $q$, the prior probability of good match quality for any banker-bank pair; $\lambda_1$, the efficiency of boutique banks; $\{a, b\}$, which control the slope and constant coefficients of the expected deal number specified in Equation 2; $\ell$, the overall speed of learning-by-doing; $\alpha$, which controls the declining marginal benefits of learning-by-doing; $\rho$, one minus the depreciation rate of human capital; and $\{\delta_0, \delta_1\}$, which capture the human capital portability in the bulge bracket and boutique sector, respectively, as shown in Equations 4 and 5. 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 as closely as possible.

First, we use the average relocation rate within each sector to identify the parameter $q$. Within-sector relocation means that a banker switches from his current employer to another employer of the same type. In our model, the efficiency parameter $\lambda$ and the portability parameter $\delta$ are identical across all employers in the same sector and thus the tradeoff between efficiency and portability should not trigger within-sector job change. Within-sector relocation is thus entirely driven by match quality. Intuitively, if the unconditional probability of a good match ($q$) is low, we should observe a higher rate of within-sector relocation.

Second, we identify the relative efficiency parameter $\lambda_1$ using the cross-sector relocation rate, or more precisely, the net labor flow into the boutique sector. Recall that we normalize the efficiency parameter $\lambda_0$ to 1 for the bulge bracket sector. Larger values of $\lambda_1$ suggest that, all else equal, human capital generates higher returns in the boutique sector, making boutique banks more attractive employers. In this case, we expect a larger fraction of bankers to transition from the bulge bracket sector to the boutique sector.

Next, we turn to the observed deal volume and use the incumbent bankers' average deal volume and the new entrants' deal volume to identify the slope and constant coefficients in Equation 2, $a$ and $b$, respectively. The deal number of new entrants are used to determine $b$ because they have not established any human capital. After $b$ is determined, $a$ can be identified using the deal volume of seasoned bankers because higher $a$ leads to more deals advised by seasoned bankers.

Learning-by-doing helps bankers build up new human capital, but the benefits from learning-by-doing is declining as bankers become more experienced. This is a common feature of many learning models, which captures the idea that low hanging fruit get picked first. Equation 12 allows for a declining marginal benefits through the parameter $\alpha$, and the larger $\alpha$ is, the faster the marginal benefits decline. We run the following regression in both the model and data:

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

and use the coefficeints $\gamma_1$ and $\gamma_2$ to help identify $\alpha$.

To identify how human capital accumulates and depreciates over time, we investigate the autocorrelation of a same banker's deal volume over different horizons. Specifically, we regress a banker's current deal number on the average number of deals he advised in the past 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 $t$. We expect to coefficients $\varrho_1$ and $\varrho_3$ to be low if bankers learn slowly and thus $\ell$ is small. In the extreme case where $\ell = 0$, human capital does not accumulate and $m_{i,t} = b$ in Equation 2. This implies that the deal number, $n_{i,t}$, follows an i.i.d Poisson process and has zero autocorrelation, which yields $\varrho_1 = \varrho_3 = 0$. We use the average of autocorrelation coefficient, $\frac{1}{2}(\varrho_1 + \varrho_3)$, to determine the parameter $\ell$.

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

Last, we identify human capital specificity (non-portability) $\delta_s$ by tracking a banker's deal volume over a 5-year event window around his job transition. 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 experienced poor prior performance are more likely to switch jobs in seek of better matches. This selection effect leads to an endogenous increase in the expected deal number post transition. The portability effect indicates that transitioning bankers will suffer from a decline in deal volume due to the loss of firm-specific human capital. We measure the overall changes of deal number around transition as:

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

where year $t$ is the year when banker $i$ employed in sector $s$ makes a career transition, and $n_{i,t+\tau}$ measures the deal number $\tau$ years after the transition.[9] The sign of $\Delta n_{s,i,t}$ can be either positive or negative, depending the relative strength of the selection effect and the portability effect. Holding everything else constant, $\Delta n_{s,i,t}$ is more negative when $\delta_s$ is larger.

# 3 Empirical Results

In this section, we match model moments to the data and present parameter estimates.

## 3.1 Model Fit

Table 2 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 in other industries, relocations are still rare events in this profession. Our model predicts that, each year, only 1.87% of bankers choose to move from a bulge bracket bank to another bulge bracket bank. The relocation rate within the boutique sector is even lower, about 1.1% per annum. These numbers line up well with their empirical counterparts, which are 2.5% and 1.08% in the data respectively. In addition, the model predicts that the net labor flow into

[9] Note that we are excluding the year of the transition in our calculation. This is avoid of the confounding effect that a banker may experience an unemployment span, which mechanically influences the number of deals that he can handle.

the boutique sector accounts for about 1.25% of the total bankers in the industry, which is close to the 0.87% observed in the data.

Empirically, bankers' deal volume is persistent over time, and our model captures this feature well. We measure the persistence using the autocorrelation coefficient of the deal number process. Specifically, we regress deal number measured in year $t$ on the average deal number measured in the past 1-2 years 3-4 years, respectively. The model implied loadings are 0.15 and 0.08, comparable to the empirical loadings of 0.16 and 0.06. The loadings are positive and the magnitudes decline with horizon. These features help us identify the parameters $\ell$ and $\rho$.

The model matches closely the average number of deals advised by bankers. The model also does a good job in matching the concave relation between deal number and bankers' total years of working experience: bankers advise more deals as they become more senior, but the benefits from learning-by-doing is declining as the bankers gain more human capital over time.

The model also matches well 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, transitionining bankers are more likely to be those who have experienced poor deal volume with the current employer, and expects an improved match quality with the new employer. This selection effect contributes to an endogenous increase in the expected deal number past transition. Second, the banker loses firm-specific human capital and needs to rebuild it over time. This portability effect leads to a decrease in the expected deal number past transition. Given that human capital portability can be different across two sectors, we measure separately the deal number change for bankers leaving a bulge bracket firm and those leaving a boutique firm. In the model, bankers who depart a bulge bracket bank advise 0.08 more deals annually compared with the pre-transition deal number, and in the data, they experience a 0.09 increase in deal number. These changes are economically sizeable compared with the average deal number of 0.8. This result also suggests that the selection effect dominates the portability effect, likely because bulge bracket employees possess more generalizable skills. In contrast, bankers who depart from boutique banks experience a decline in deal volume post transition, with a magnitude of 0.10 in the model and 0.06 in the data. This result suggests that the loss of firm-specific human capital makes transition highly costly for employees in the boutique sector.

Lastly, we examine a few important moments that are not explicitly targeted in the SMM system. We use them to validate the model because they reflect the main tradeoff in the model and emerge as the central predictions of the equilibrium. Figure 4 illustrates the relationship between a banker's mobility and his seniority. We measure banker seniority using the total years of work experience in the industry. The blue solid line plots the model predicted value while the gray dots plot the data observations. We find that mobility, defined as the likelihood of banker job change, declines monotonically with a banker's seniority in the data, and the model implied mobility follows a very similar pattern. During the first 5 years of a banker's career, the relocation rate is about 7% each year. The relocation rate drops by half after 20 years of experience.

There are two reasons why this happens in our model. First, bankers learn about their match quality gradually over time and switch employers if they perceive the existing match as low. As as a banker becomes more senior, he is more likely to have already encountered a good match. Second, a senior banker has accumulated more non-portable human capital with his current employer. The potential loss of firm-specific skills makes job transition costly and reduces the banker's incentives to switch employers.

### 3.2 Parameter Estimates

Table 3 reports the parameter estimates. Panel A presents the calibrated parameters as discussed in Section 2.2. These parameters are less model-specific, so we calibrate them outside of the model to ensure that these parameter choices are consistent with the observed data characteristics and the consensus in the literature.

Panel B of Table 3 reports the point estimate and standard errors for the 9 model parameters. The probability of good match, $q$, is estimated to be around 0.46. It suggests that good match and bad match are almost equally likely. This means that, at the start of each job span, bankers face high level of uncertainty about match quality. Their ability to learn is thus critical for them to distinguish good matches from bad ones.

We estimate $\lambda_1$, the efficiency of boutique banks, to be 1.032. Given that the efficiency of bulge bracket banks, $\lambda_0$, is normalized to be one, our estimate indicates that boutique advisors on average generate 3.2% more profits from advising each deal. Higher efficiency in the boutique sector can arise for two reasons. First, previous studies show that the reputation and quality of M&A advisors affect their ability to create value in advising M&A deals (see e.g., Kale et al. (2003), Bao and Edmans (2011), Golubov et al. (2012), and Chemmanur et al. (2019)). Close to our setting, Gao et al. (2019) document that boutique banks create 1-2% higher announcement returns for their clients than bulge bracket banks. If higher value creation is rewarded with higher advisory fees, our estimate of $\lambda_1$ seems consistent with the docuamented value creation by boutique banks. Second, anecdotal evidence suggests that bulge bracket banks incur high overhead costs due to their large-scale, diverse operations. As the costs rise, profits decline, rendering $\lambda_0$ lower than $\lambda_1$.

The slope parameter in Equation 2, $a$, is estimated to be 0.975. Given that we normalize $c$ to be one in the equation, this estimate suggests that the expected deal number produced by a good match almost doubles that produced by a bad match. This finding highlights the importance of match quality. Note that a higher productivity of human capital increases not only the number of deals advised within one period but also the speed of human capital accumulation through Equation 4 and 5. Human capital accumulation in turn propels future deal generation. The effect of high productivity, therefore, is amplified and persists in the long run. The constant parameter in Equation 2, $b$, is estimated to be 0.188. This parameter controls the deal volume independent of human capital and it determines the average number of deals advised by novice bankers in their first year of employment.

Our estimate of human capital persistence, $\rho$, is 0.883. Compared with the capital depreciation rate, which is about $15 - 25\%$ per annum as commonly used in the literature, human capital in the M&A advisory industry is more persistent. This finding seems plausible, because a large part of investment banking business requires tacit skills such as relationship building with clients, and such skills barely become obsolete once acquired. Other codified skills such as deal valuation and due diligence investigation have evolved slowly over the past decades since business schools started teaching them in standard courses for undergraduate and MBA students (see e.g., Morrison and Wilhelm (2007)). As a result, for an industry in which technology develops slowly over time, we expect human capital to be persistent.

Last, we find that human capital portability differs significantly across the bulge bracket sector and the boutique sector. Based on our estimates, for bankers working in a bulge bracket firm, 88% of the human capital they accumulate is portable and only 12% is non-portable. However, only 56% of the human capital acquired by boutique firm employees is portable. This difference in human capital portability, paired with the difference in efficiency, constitutes the main tradeoff that bankers face in making career choices between bulge bracket and boutique firms.

# 4 Model Implications

In this section, we analyze additional implications from the model. First, we examine how the nonportable human capital interacts with early-career luck and affects the efficiency of labor allocation. In doing so, we pinpoint scenarios whereby good luck does not necessarily benefit a banker, but instead delays efficient job separation and negatively affects the banker's career outcome in the long run. Second, we conduct counter-factual experiments to quantify the effects of nonportable human capital and unobservable match quality on worker career and performance. Lastly, we discuss the role of human capital portability in shaping industry structure.

## 4.1 The Role of Luck

Several studies have examined the role of luck in determining executive compensation and CEO turnover (Bertrand and Mullainathan (2001); Jenter and Kanaan (2015)). Relatedly, Oyer

(2006) studies the career outcomes of fresh economic PhDs and finds that those graduating in favorable "climate" tend to have better research productivity in the long term. While the empirical findings suggest that luck can have prolonged real effects on career outcomes, less is known regarding the underlying mechanisms. In this section, we examine how luck affects a banker's career outcome and long-term productivity. Our setup is particularly suitable for this analysis for two reasons: First, our simulation approach allows us to to keep all else constant and pinpoint the effect of luck on bankers' career trajectories; Second, relying on the estimated model parameters ensures that our simulated results are empirically relevant.

Luck affects a banker's career outcomes through two main channels. First, it affects the number of deals a banker advises each period as well as the resulting human capital accumulation. Bankers benefit from good luck unambiguously through this channel. Second, luck influences a banker's perception about his match quality with the current employer. Good luck makes a banker overly optimistic about the match quality, especially if it happens in the early stage of the banker's career, when he relies on only a few signals to infer match quality. As good luck leads to over-optimism, it could delay efficient job transition, which in turn affects a banker's career outcomes and productivity in the long-run.

We first analyze the effect of initial match quality on an average banker's career outcome. It serves as the benchmark for our experiment. Panel A of Table 4 presents the results. We examine four variables including banker human capital, mobility (i.e., the likelihood of job transition), average deal number per annum, and the employment value (i.e., the value function defined in Equation 7). We partition a banker's career path into five stages using the years of working experience: 0-4 years, 5-10 years, 11-20 years, 20-30 years, and 30-40 years. In each stage, we compare an average banker who starts with a good initial match with the one who starts with a bad initial match. As expected, the banker with good initial match accumulates more human capital, advises a larger number of deals, and creates a higher employment value over his career.

One may expect that the effect of the initial match quality would gradually die out over time, because bankers can freely switch their employers once they learn about the low initial match quality. In contrast, we find that the initial match quality generates a persistent effect, which peaks around a banker's mid-career (i.e., 11-20 years). For example, the average banker with a good initial match advises about 0.2 more deals (or 32% more) during his mid-career stage than the average banker with a bad initial match quality. The two bankers also differ in their employment values by about 7% during the mid-career stage. The effects of the initial match quality do not wear off even in the late-career stage (30-40 years), with the gaps in deal number and employment value being 0.1 (10%) and 0.04 (4%), respectively. In sum, the quality of the first job generates a nearly permanent effect on bankers' productivity.

This persistent effect stems from the delayed learning process about true match quality, and the existence of firm-specific skills. Bankers gradually learn about the match quality over time. By the time of they realize that the match quality with the current employers is low, they have already accumulated a non-trivial amount of specific human capital. The loss of such human capital is particularly costly for a banker in the mid- or late-career stage of his career. Consistently, we find that the initial match quality has a persistent effect on banker mobility rate, with the largest effect being in the mid-career stage.

Now we add luck into the model. Specifically, we simulate another set of bankers following the same setup as in Panel A but alter the setting by changing only one input: we let the bankers receive one extra deal in the first four years of his career. Given that the average number of deal per banker per year averages 0.8 in our sample, one extra deal represents a meaningful performance boost for junior bankers.

Panel B of Table 4 shows that good luck amplifies the effects of initial match quality on bankers' late-career outcomes. To see this, recall that the average banker with a good initial match generates 0.2 more deals per year in his mid-career stage and 0.1 more deals in the late-career stage than the average banker with a bad initial match. With early-career luck, the good-match banker generates 0.5 more deals early in his career and 0.3 more deals later in his career than the bad-match banker (who also has early-career luck). We observe a similar effect on employment value. This amplification effect occurs because good luck makes the banker overly optimistic about his initial match quality and reduces his transition likelihood. Consistently, we find that both bankers exhibit lower mobility during early career stages. For the good-match banker, luck reduces the likelihood of erroneous transition, accelerates human capital buildup, and leads to higher employment value throughout his career. Yet, with a bad initial match, good luck interferes with the banker's learning about the low match quality and delays efficient job separation. A prolonged job span with a poorly matched employer leads to slow accumulation of human capital and a greater human capital loss during late-career transitions. In this case, the lucky banker exhibits higher mobility, but lower performance and employment value late in his career (21 years onward).

Overall, analyses in this section suggest that match quality can have persistent effects on a banker's career outcomes and productivity, and learning about match quality plays an important role in driving these results. Good luck may not always benefit a banker because it clouds the banker's perception of match quality and can delay efficient job transition. Such a delay is particularly costly with the presence of nonportable human capital.

### 4.2 Frictions and Counterfactuals

In this section, we quantify the effects of unobservable match quality and nonportable human capital on worker career outcomes. We do so by conducting counterfactual analyses, removing one friction at a time. While these labor-market frictions cannot be completely eliminated in reality, the counterfactual analyses provide valuable policy implications. For example, the estimated model allows us to examine the efficiency improvement from providing additional signals regarding match quality to the employees in a timely manner. This can be done via a more transparent and informative performance evaluation system. In addition, the portability of banker human capital can be improved by codifying and standardizing some investment banking skills. This is partly the reason why many business schools in the past decades have pushed towards a combination of quantitative analysis and case studies in their curriculum (Morrison and Wilhelm (2007)).

We carry out three counterfactual analyses in Table 5. In Panel A, we present the baseline model predictions on banker human capital, mobility, average number of deals advised each year, and the employment value. As in Table 4, we partition a banker's career path into five stages. In the baseline model, we observe that human capital, deal volume, and employment value increase with work experience and stabilize after 20 years. Mobility is high in the first 10 years and declines gradually over time.

In Panel B, we create a counterfactual scenario in which match quality is immediatley observable upon employment. In this scenario, an average banker experiences a 3-4% increase in his human capital, a 7-12% increase in deal volume, and a 5-10% increase in employment value. Two reasons contribute to such an improvement. First, the banker leaves a poorly matched employer sooner and thus accumulates human capital more rapidly over time. Second, as the banker relocates more quickly, less firm-specific human capital is lost during job transitions. This counterfactual analysis suggests that information frictions regarding match quality have a pronounced effect on banker productivity and employment value.

In Panel C, we consider a scenario in which all human capital is portable. Bankers are better off in this setting. For example, the average banker experiences a 3% in human capital increases and 5% increase in employment value. Notably, the mobility curve is now backloaded, peaking during the 11-20 year range and maintaining high values in later years. This happens because bankers are not concerned about losing firm-specific human capital. They are more patient in learning about match quality in early years and switch jobs more frequently in later years.

In Panel D, we eliminate both frictions and present a scenario with both perfect information about match quality and perfectly portability. All bankers benefit from this scenario, especially junior ones. To see this, employment value increases by 12% for junior bankers (below 10 years of experience) and by 7% for senior bankers (over 30 years of experience). This is because learning about match quality and human capital portability are both more important for junior bankers. Importantly, after removing one friction, the marginal effect of removing the second friction becomes significantly smaller. For example, for a banker in his mid-career stage (11-

20 years), removing information friction alone increases his employment value by 9.1% and removing the portability friction alone increases his employment value by 5.5%. However, when both frictions are removed, employment value goes up by only 11.5%. This finding suggests that the two frictions are complementary: when one friction is eliminated, the detrimental effect of the other friction is also reduced (so eliminating the other friction generates a weaker effect). The complementarity between the two frictions arises from the fact that slow learning of match quality prolongs the duration poorly matched employment. As a result, bankers build up more non-portable human capital, which is lost upon future job transition.

### 4.3 Industry Structure

In the last step of our analysis, we examine how the portability gap across firms influences the labor market share of the two sectors. We do so by simulating bankers' career choices under different values of the portability gap. We define portability gap as the difference between the human capital portability of the bulge bracket sector and that of the boutique sector (i.e, $\delta_1 - \delta_0$). We adjust the value of this portability gap while keeping all other parameters unchanged in the model. We then track labor flows in and out of the boutique sector over a 20-year period. At time 0, the boutique sector contains a randomly selected 10% of bankers in our sample.

Figure 5 depicts the results from the simulation analysis. The x-axis indicates the number of years that have elapsed in the simulation and the y-axis indicates the proportion of bankers working in the boutique sector in a given year. Each line indicates a distinct value of the portability gap. As expected, a smaller portability gap is associated a larger labor share for the boutique sector, because the lack of human capital portability in that sector makes it difficult to attract talent. With a 50% reduction in the portability gap, over 70% of the bankers migrate to boutique firms over the 20-year horizon. In contrast, a 50% increase in the sectoral portability gap diminishes the boutique firm labor share to only 2%. Overall, results from this analysis suggest that the heterogeneity of human capital portability across firms is a key determinant of industry structure.

## 5 Conclusion

We examine how human capital portability affects M&A advisors' career choices between bulge bracket banks and boutique banks. We build and estimate a dynamic model in which bankers accumulate both general and firm-specific human capital through their deal advising experience. Bankers trade off between the opportunity to accumulate more general human capital in bulge bracke banks and a higher return to skill in boutique banks. Learning about unobservable match quality creates another friction that makes this tradeoff particularly important for bankers' long-run career outcomes. Estimating the model to match granular data on M&A advisors' career trajectories, we find that bankers have different preferences over the two sectors of banks along their career paths — novice bankers value more human capital portability and thus prefer working in bulge bracket banks, while senior bankers put more weight on efficiency and thus prefer working in boutique banks. Such a difference explains why bankers are more likely to choose bulge bracket banks at the start of their careers but increasingly migrate to boutique banks when they become more seasoned. The low portability of human capital in boutique banks also discourages high-quality bankers from joining them, thus hindering the allocation of skilled labor to more productive sectors of the industry. Our study contributes to existing research by quantifying the portability of human capital in labor skill-dependent industries and the variation of portability across firm organization structures. It also speaks to how human capital portability influences the optimal allocation of skilled labor in an industry.

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Figure 1: Labor Mobility: The Effect of Human Capital and Match Quality

This figure illustrates the mobility of individual bankers with different levels of human capital and perceived match quality in a heatmap. Labor mobility is measured as the 5-year cumulative probability of job change by individual bankers. Panel A shows the results for the bulge bracket sector and Panel B shows the results for the boutique sector. x-axis is the perceived match quality $p$ and y-axis is the total human capital $H = h + \omega$. The color scales indicate labor mobility, with lighter color indicating higher mobility.

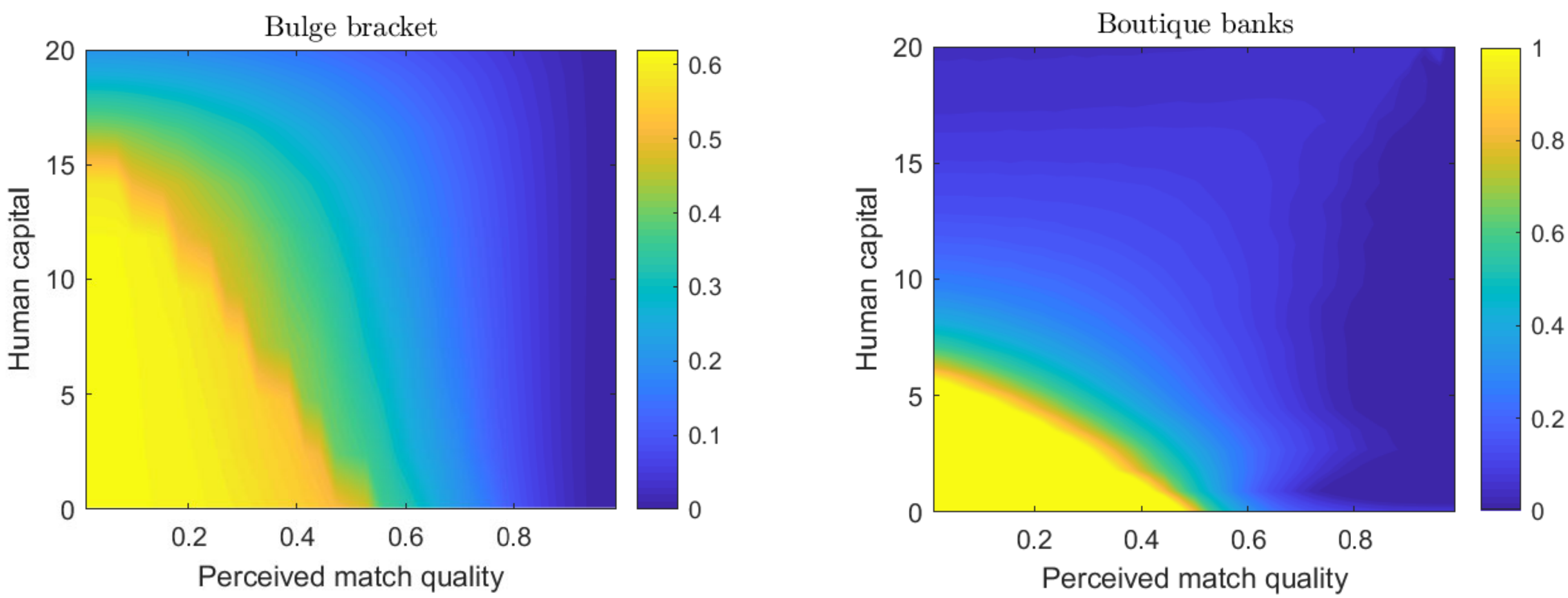

Figure 2: Portability Premium

This figure shows how bankers value portable human capital relative to nonportable human capital. We plot the relation between perceived match quality, existing human capital, and portability premium. Portability premium is defined as the relative difference between the marginal value of portable human capital and the marginal value of non-portable human capital, as in equation13. Panel A shows the results for the bulge bracket sector and Panel B 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 portability premium.

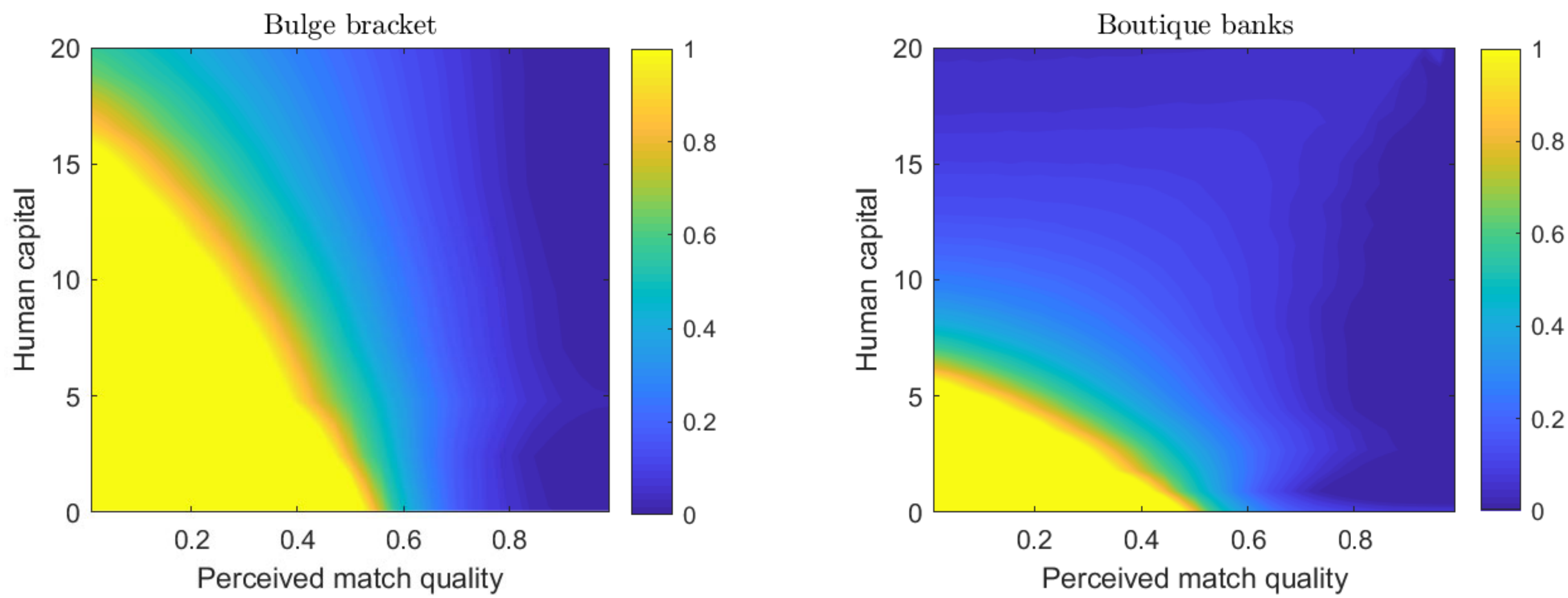

Figure 3: Sector Choices: Who Works for Whom?

This figure shows the share of workers with a given level of work experience that work for boutique firms. We simulate a panel of bankers who start their career in bulge bracket firms and track the fraction of these bankers switching to boutique firms over their career path. The x-axis is the number of years the bankers have worked in the industry and y-axis is the fraction of these bankers who already switched to boutique firms.

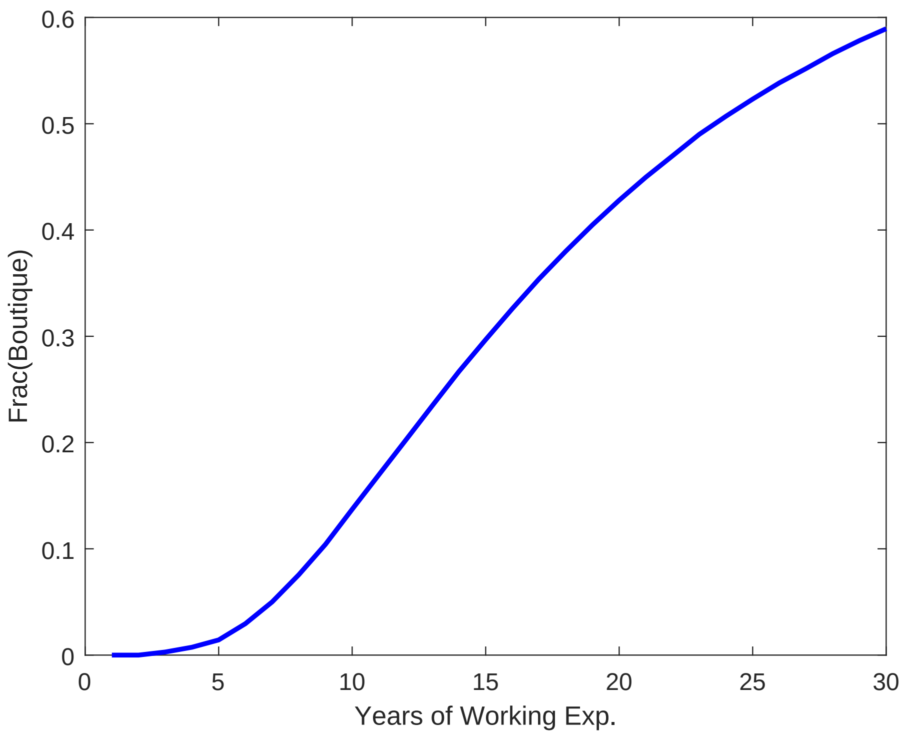

Figure 4: Mobility and Banker Seniority

This figure illustrates the relation between a banker's mobility and his seniority. Mobility is defined as the banker's likelihood of job switch in a given year, and seniority is defined as his total years of working experience by the year of interest. The blue solid line is the model implied mobility and the gray dots are the mobility measured in data.

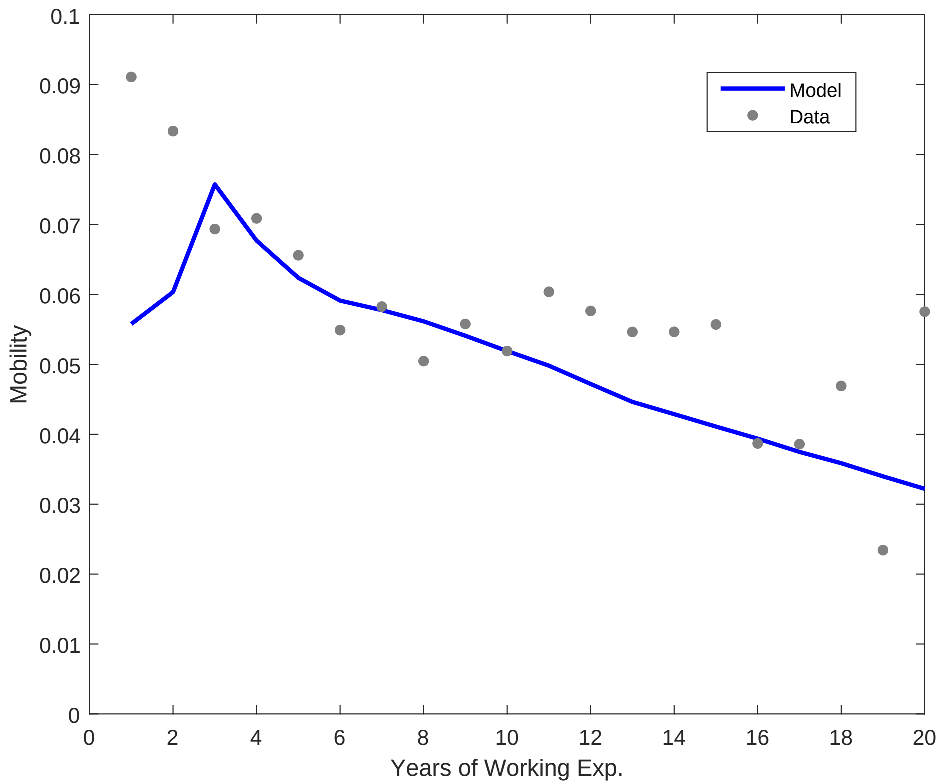

Figure 5: Human Capital Portability Gap and Boutique Bank Market Share

This figure shows how the market share for boutique banks will evolve when the human capital portability gap between the bulge bracket and boutique sectors is increases or decreases by 25% and 50%, respectively.

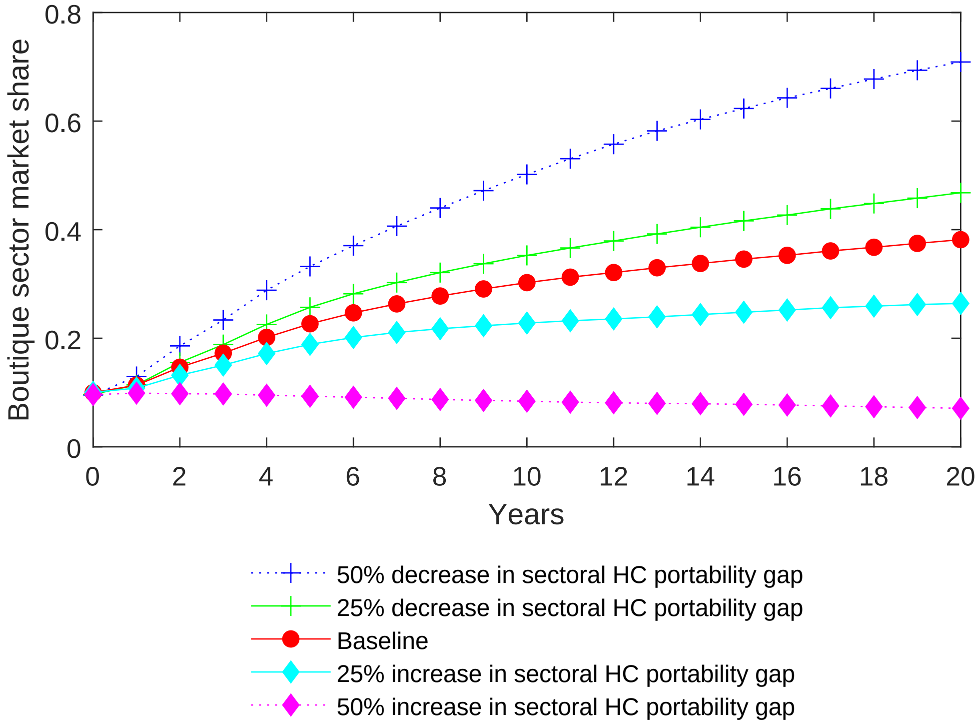

Table 1: Moment Construction and Variable Definition

This table provides the definition for variables and moments used in the paper. These moments are used as targeted moments in the SMM, as reported in Table 2.

| 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 banekrs employed by all banks |
| Loading of deal number on avg. past 1-2 yr deal number | Coefficient from 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 $t-2$, coefficient $\varrho_1$ in Equation 15 |
| Loading of deal number on avg. past 3-4 yr deal number | Coefficient from 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 $t-4$, coefficient $\varrho_3$ 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 from regressing the number of deals advised by a banker in year $t$ on the banker's total years of working experience as a M&A advisor, coefficient $\gamma_1$ in Equation 14 |
| Loading of deal number on banker years of experience squared | Coefficient from 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 a M&A advisor, coefficient $\gamma_2$ 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 a M&A advisor |
| Deal num. chg. around banker transition from bulge bracket | Change in 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 3-yr average deal number as a banker leaves a boutique bank, as in Equation 16 |

Table 2: Model Fit

This paper shows how well the model fits 8 targeted moments (i.e., moments used in SMM): the relocation rate within the bulge bracket (boutique) sector is defined as the total number of bankers who switch from a bulge bracket (boutique) bank to another bulge bracket (boutique) bank diveded by the total number of bankers in the economy; the net labor flow into the boutique sector is the relocation rate from bulge bracket banks to boutique banks minus the relocation rate from boutique banks to bulge bracket banks; the average deal number per banker per year is the average number of deals advised by bankers in our sample each year across the whole sample period; loading of the deal number on 2-year (5-year) lagged deal number is the regression coefficient $b_2$ ($b_5$) obtained from Equation 15; and the deal number change around banker transition from the bulge bracket (boutique) sector is estimated as the average of $\Delta n_{i,s,t}$ in Equation 16 across all bankers departing from the bulge bracket (boutique) sector.

| Moment | Data | | Model |
| --- | --- | --- | --- |
| | Empirical value | Standard error | Simulated value |
| Relocation rate within the bulge bracket sector | 0.0187 | 0.0028 | 0.0249 |
| Relocation rate within the boutique sector | 0.0109 | 0.0014 | 0.0108 |
| Net labor inflow into the boutique sector | 0.0087 | 0.0017 | 0.0125 |
| Loading of deal number on avg. past 1-2 yr deal number | 0.1511 | 0.0269 | 0.1593 |
| Loading of deal number on avg. past 3-4 yr deal number | 0.0803 | 0.0347 | 0.0628 |
| Avg. deal number per banker per year | 0.8034 | 0.0490 | 0.7918 |
| Loading of deal number on banker years of experience | 0.1269 | 0.0056 | 0.1207 |
| Loading of deal number on banker years of experience squared | -0.0026 | 0.0003 | -0.0029 |
| Avg. deal number per new entrant per year | 0.2145 | 0.0274 | 0.1971 |
| Deal num. chg. around banker transition from bulge bracket | 0.0800 | 0.0447 | 0.0915 |
| Deal num. chg. around banker transition from boutique | -0.1005 | 0.0549 | -0.0565 |

Table 3: Parameter Estimates

This table reports the parameter estimates. Panel A contains the parameters calibrated or normalized. Panel B presents the parameter estimates obtained from the SMM, together with the estimation standard errors. $\beta$ is the discount rate, $\eta$ is the exogenous exit rate of bankers, $\lambda_0$ is the efficiency of bulge bracket banks that is normalized to 1, $c$ is a parameter that affects the expected deal number as in Equation 2 and we normalize $c$ to 1 because it cannot be separately identified from $\ell$. $q$ is the probability of having a good match, $\lambda_1$ is the efficiency of boutique banks, $\alpha$ controls the marginal benefits of learning-by-doing in Equation 12, $a$ and $b$ are the slope and constant parameter in Equation 2 that determines the expected deal number, $\ell$ is the parameter that controls the overall speed of learning-by-doing in Equation 12, $\rho$ is the persistence of human capital, and $\delta_0$ and $\delta_1$ are human capital portability in the bulge bracket and boutique sector, respectively.

| Panel A. Calibrated/Normalized Parameters | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Calibration | | | | | Normalization | | | |
| | $\beta$ | $\eta$ | | | | $\lambda_0$ | $c$ | | |
| Value | 0.90 | 0.04 | | | | 1 | 1 | | |
| **Panel B. Estimated Parameters** | | | | | | | | | |
| | $q$ | $\lambda_1$ | $\alpha$ | $a$ | $b$ | $\ell$ | $\rho$ | $\delta_0$ | $\delta_1$ |
| Estimate | 0.460 | 1.032 | 0.793 | 0.975 | 0.188 | 0.325 | 0.883 | 0.116 | 0.440 |
| Standard errors | 0.139 | 0.011 | 0.201 | 0.489 | 0.023 | 0.102 | 0.083 | 0.042 | 0.078 |

Table 4: The Role of Luck

This table presents the effect of luck on bankers' career outcomes and productivity. We examine a banker's human capital, mobility (the likelihood of job change), average deal number per annum, and employment value (i.e., the value function in Equation 7) along his career path, which we divide into five stages by the years of working experience:1-4 years, 5-10 years, 11-20 years, 21-30 years, and 31-40 years. Panel A compares an average banker with high initial match quality with an average banker with low initial match quality. Panel B compares a lucky banker with high initial match quality with a lucky banker with low initial match quality.

| Panel A. The Effect of Initial Match Quality | | | | | |
|---|---|---|---|---|---|
| | 0-4yr | 5-10yr | 11-20yr | 21-30yr | 31-40yr |
| High initial match quality | | | | | |
| Human capital | 0.286 | 0.881 | 1.380 | 1.567 | 1.627 |
| Mobility | 0.109 | 0.112 | 0.088 | 0.073 | 0.063 |
| Deal number | 0.226 | 0.545 | 0.806 | 0.904 | 0.952 |
| Employment Value | 0.518 | 0.681 | 0.839 | 0.914 | 0.950 |
| Low initial match quality | | | | | |
| Human capital | 0.257 | 0.741 | 1.229 | 1.475 | 1.566 |
| Mobility | 0.110 | 0.123 | 0.110 | 0.090 | 0.076 |
| Deal number | 0.182 | 0.360 | 0.609 | 0.781 | 0.868 |
| Employment Value | 0.517 | 0.647 | 0.783 | 0.868 | 0.914 |
| Difference in productivity and valuation | | | | | |
| Deal number | | 0.185 | 0.197 | 0.123 | 0.084 |
| Employment Value | | 0.034 | 0.056 | 0.046 | 0.036 |
| Deal number (%) | | 51.32 | 32.31 | 15.74 | 9.63 |
| Employment Value (%) | | 5.25 | 7.10 | 5.23 | 3.95 |

| Panel B. The Effect of Luck | | | | | |
|---|---|---|---|---|---|
| | 0-4yr | 5-10yr | 11-20yr | 21-30yr | 31-40yr |
| Good luck and high initial match quality | | | | | |
| Human capital | 1.503 | 1.844 | 1.740 | 1.723 | 1.723 |
| Mobility | 0.040 | 0.041 | 0.045 | 0.046 | 0.045 |
| Deal number | 1.583 | 1.280 | 1.079 | 1.062 | 1.064 |
| Employment Value | 0.806 | 1.020 | 1.010 | 1.014 | 1.020 |
| Good luck and low initial match quality | | | | | |
| Human capital | 1.425 | 1.654 | 1.466 | 1.485 | 1.532 |
| Mobility | 0.040 | 0.050 | 0.089 | 0.093 | 0.083 |
| Deal number | 1.377 | 0.791 | 0.616 | 0.709 | 0.795 |
| Employment Value | 0.800 | 0.942 | 0.865 | 0.869 | 0.893 |
| Difference in productivity and valuation | | | | | |
| Deal number | | 0.489 | 0.463 | 0.353 | 0.269 |
| Employment Value | | 0.078 | 0.144 | 0.145 | 0.127 |
| Deal number (%) | | 61.85 | 75.23 | 49.81 | 33.82 |
| Employment Value (%) | | 8.31 | 16.61 | 16.65 | 14.24 |

Table 5: Frictions and Counterfactual Analyses

This table presents the results for the baseline model and three counterfactual exercises in which we eliminate frictions in the labor market. Panel A shows the baseline results. Panel B shows the results when the match quality is assumed to be perfectly revealed upon the formation of each match (no information friction). Panel C shows the results when human capital is assumed to be fully portable (no portability friction). Panel D shows the results when both information and portability frictions are removed. We examine a banker's human capital, mobility (the likelihood of job change), average deal number per annum, and employment value (i.e., the value function in Equation 7) along his career path, which we divide into five stages by the years of working experience:1-4 years, 5-10 years, 11-20 years, 21-30 years, and 31-40 years.

| | 0-4yr | 5-10yr | 11-20yr | 21-30yr | 31-40yr |
|---|---|---|---|---|---|
| Panel A. Baseline Model | | | | | |
| Human capital | 0.271 | 0.810 | 1.305 | 1.520 | 1.596 |
| Mobility | 0.110 | 0.117 | 0.099 | 0.082 | 0.070 |
| Deal number | 0.203 | 0.454 | 0.706 | 0.843 | 0.906 |
| Employment Value | 0.518 | 0.664 | 0.811 | 0.890 | 0.931 |
| Panel B. Perfect Information | | | | | |
| Human capital | 0.271 | 0.830 | 1.365 | 1.586 | 1.651 |
| Mobility | 0.108 | 0.092 | 0.074 | 0.063 | 0.056 |
| Deal number | 0.205 | 0.487 | 0.791 | 0.928 | 0.980 |
| Employment Value | 0.573 | 0.734 | 0.885 | 0.953 | 0.980 |
| Panel C. Perfect Portability | | | | | |
| Human capital | 0.274 | 0.825 | 1.341 | 1.565 | 1.640 |
| Mobility | 0.044 | 0.088 | 0.106 | 0.091 | 0.080 |
| Deal number | 0.203 | 0.459 | 0.723 | 0.864 | 0.926 |
| Employment Value | 0.541 | 0.700 | 0.856 | 0.938 | 0.977 |
| Panel D. Perfect Information and Portability | | | | | |
| Human capital | 0.274 | 0.846 | 1.390 | 1.614 | 1.679 |
| Mobility | 0.105 | 0.082 | 0.077 | 0.068 | 0.062 |
| Deal number | 0.206 | 0.493 | 0.801 | 0.944 | 0.993 |
| Employment Value | 0.583 | 0.748 | 0.904 | 0.974 | 1.000 |

# A A simplified model

If the match quality is good, then the banker stays with the same bank forever. Each period, he advises $n_t = (a \cdot \mu + c) \cdot (h_t + \omega_t) + b$. Note that we assume $c = 0$ in the simplified model and $\mu = 1$ when the match quality is good, so

$$\begin{aligned} n_t &= a \cdot (h_t + \omega_t) + b \\ &= a \cdot H_t + b \end{aligned} \tag{A.1}$$

where $H_t = h_t + \omega_t$ is the total human capital. Without job switch in the future, portable and non-portable human capital play the same role in the value function, and therefore we only need to track the total human capital in this case. The banker's continuation value is:

$$U_s = \sum_{t=1}^{\infty} \beta^{t-1} \lambda_s \left(a \cdot H_{t+1} + b\right) \tag{A.2}$$

and $H_{i,t}$ follows the law of motion:

$$\begin{aligned} H_{t+1} &= \rho \cdot H_t + \ell \cdot n_t \\ &= (\rho + a\ell) \cdot H_t + \ell \cdot b \end{aligned} \tag{A.3}$$

The second step follows by substituting in Equation A.1. To make human capital a stationary process, we assume $0 < \rho + a\ell < 1$, and we can rewrite Equation A.3 as:

$$\begin{aligned} H_{t+1} - \overline{h} &= \phi \left(H_t - \overline{h}\right) \\ &= \phi^{t-1} \left(H_2 - \overline{h}\right) \end{aligned} \tag{A.4}$$

where

$$\phi = \rho + a\ell$$
$$\overline{h} = \frac{\ell b}{1 - (\rho + a\ell)}$$

Substituting Equation A.4 into Equation A.2, we can solve for $U_s$, which is the capitalized value of all future deal advising profits after the banker settles down with a bank:

$$\begin{aligned} U_s &= \sum_{t=1}^{\infty} \beta^{t-1} \lambda_s \left(a \cdot H_{t+1} + b\right) \\ &= \lambda_s \left(a\overline{h} + b\right) \sum_{t=1}^{\infty} \beta^{t-1} + \lambda_s a \sum_{t=1}^{\infty} \left[\beta^{t-1} \phi^{t-1} \left(H_2 - \overline{h}\right)\right] \\ &= \frac{\lambda_s \left(a\overline{h} + b\right)}{1 - \beta} + \frac{\lambda_s a \left(H_2 - \overline{h}\right)}{1 - \beta\phi} \\ &= \lambda_s \left[\frac{\left(a\overline{h} + b\right)}{1 - \beta} + \frac{a \left(\left(\rho + a\ell\right) \cdot h + b\ell - \overline{h}\right)}{1 - \beta \left(\rho + a\ell\right)}\right] \end{aligned} \tag{A.5}$$

The second step follows by substituting in Equation A.4, and the last step follows because $H_2 = \rho h + \ell (ah + b)$ is the banker's human capital at the beginning of period two if the initial match quality is good.

If match quality is bad, the banker switches to a new bank in the same sector and draws a new match quality. He then faces the same situation as in the first period except that his portable human capital becomes $\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b$ and non-portable human vanishes upon transition. his continuation value, therefore, is equal to $V_s \left(\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b\right)$.

Combining the two possible situation, we can write down the Bellman equation as

$$V_s(h) = \lambda_s \left(a \cdot q \cdot h + b\right) + \beta \left[q \cdot U_s + (1 - q) V_s \left(\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b\right)\right]$$

where the first term on RHS is the expected profits this period and the second term is the expected continuation value. Applying Taylor expansion to $V_s(h)$, we solve for $V_s(h)$:

$$V_s(h) = \frac{\lambda_s\left(a \cdot q \cdot h + b\right)}{1-\beta(1-q)} + \frac{\beta q \cdot U_s}{1-\beta(1-q)} + \frac{\beta(1-q)}{1-\beta(1-q)}\frac{dV_s(h)}{dh}\left[(1-\delta_s)\cdot \ell \cdot b - (1-\rho)h\right] \quad \text{(A.6)}$$

In the simplified model, the banker's career path contains two stages: before landing on a good match, he switches employers each period, and we define this period as his *career transition period*; and upon a good match, he stays with the employer forever, and we define this period as his *long-term career period.* The value function in Equation A.6 contains three components: the first term is the capitalized profits from deal advising during the career transition period; the second term is the capitalized profits from deal advising during the long-term career period; and the third term is the capitalized value arising from changes in human capital before reaching the long-term career period. It captures the value added through accumulating more portable human capital from learning-by-doing and the value lost through human capital depreciation, where $\frac{dV_s(h)}{dh}$ is the "price" of portable human capital.

We conjecture a linear functional form of $V_s(h) = B_0 + B_1 h$ and thus $\frac{dV_s(h)}{dh} = B_1$. We subtitute them into Equation A.6 and solve for the coefficients:

$$\begin{aligned} B_1 &= \frac{a \cdot q \cdot \lambda_s}{\left(1-\rho\beta(1-q)\right)\left(1-\beta(\rho+a\ell)\right)} \\ B_0 &= \frac{\lambda_s}{1-\beta(1-q)}\left[b + \beta q\left(\frac{a\overline{h}+b}{1-\beta} + \frac{ab\ell - a\overline{h}}{1-\beta(\rho+a\ell)}\right) + \frac{\beta(1-q)b\ell aq(1-\delta_s)}{\left(1-\rho\beta(1-q)\right)\left(1-\beta(\rho+a\ell)\right)}\right] \end{aligned}$$

To facilitate our analysis of the tradeoff between efficiency and portability, we can rewrite $V_s(h)$ as

$$V_s(h) = \lambda_s\left(A_0 + A_1(1-\delta_s) + A_2 h\right) \quad \text{(A.7)}$$

where

$$A_0 = \frac{1}{1-\beta(1-q)}\left[b + \beta q\left(\frac{a\overline{h}+b}{1-\beta} + \frac{ab\ell - a\overline{h}}{1-\beta(\rho+a\ell)}\right)\right] \tag{A.8}$$

$$A_1 = \frac{1}{1-\beta(1-q)}\left[\frac{\beta(1-q)b\ell aq}{(1-\rho\beta(1-q))\,(1-\beta(\rho+a\ell))}\right] \tag{A.9}$$

$$A_2 = \frac{aq}{(1-\rho\beta(1-q))\,(1-\beta(\rho+a\ell))} \tag{A.10}$$

Given that $\rho$, $\beta$, $q$, and $\rho + a\ell$ all fall in the interval of $(0, 1)$ and $a$, $b$, $\ell$, and $\lambda_s$ are all positive, it is easy to verify $A_1 > 0$ and $A_2 > 0$. For $A_0$, since $1 - \beta < 1 - \beta(\rho + a\ell)$,

$$\frac{a\overline{h}+b}{1-\beta} + \frac{ab\ell - a\overline{h}}{1-\beta(\rho+a\ell)} > \frac{a\overline{h}+b}{1-\beta(\rho+a\ell)} + \frac{ab\ell - a\overline{h}}{1-\beta(\rho+a\ell)} > 0$$

and thus $A_0 > 0$ holds as well.

# B Fee-adjusted Deal Number

To construct the fee-adjusted deal number, we first collect the advisory fee data from SDC database for all M&A deals from 1980 to 2018. Advisory fees are reported separately for acquirer and target financial advisors, and the data is thinly populated. We deflate both advisory fee and deal value using US GDP deflator to convert them into real value. We then create a variable $FeePct = \frac{Fee}{DealVal}$ as the advisory fee as a percent of deal value and plot it against the logarithm of real deal value in Figure 6. In this figure, we group deals into 15 bins based on deal value and then calculate the average fee percent and logarithm of deal value within each bin. Fee percent and log deal value exhibits a strong linear relationship with a negative slope.

We then run the following OLS regression using all deals with non-missing observed advisory fee data:

$$FeePct_{m,j} = a_m + b_m \cdot ln(DealVal_j) + \varepsilon_{m,i} \tag{A.1}$$

where $m$ indicates fee paid by the acquirer or target and $j$ indicates the deal with non-missing fee data. Using the regression coefficients obtained from Equation A.1 and the deal value observed in deals with missing fee data, we calculate a predicted advisory fee for these deals:

$$\hat{FeePct}_{m,i} = a_m + b_m \cdot ln(DealVal_i)$$
$$\hat{Fee}_{m,i} = \hat{FeePct}_{m,i} \cdot DealVal_i$$

where we first calculate the predicted fee percent and then convert it to the dollar value of advisory fee. We compute a per-capita advisory fee as:

$$FeePCP_{m,i} = \begin{cases} \frac{Fee_{m,i}}{N_{m,i}} & if\ Fee\ availble \\ \frac{\hat{Fee}_{m,i}}{N_{m,i}} & if\ Fee\ unavailble \end{cases}$$

where the observed fee or the predicted fee (when fee is unavailable in the data) is scaled by the total number of bankers working for the acquirer/target, $N_{m,i}$. $FeePCP$ captures the average advisory fee paid to each banker who worked on the deal.

For deals with missing deal value data, we cannot calculate the predicted fee.

We construct the fee-adjusted deal number following the steps below:

1. For deals without $FeePCP$, we just count them as one deal;

2. Among deals with $FeePCP$, we obtain the sample median of $FeePCP$ across all observations, denoted as $MED_{FeePCP}$.

3. For deals whose $FeePCP$ is below $MED_{FeePCP}$, we count them as one deal;

4. For deals whose $FeePCP$ is above $MED_{FeePCP}$, we use the following equation to calculate the fee-adjusted deal number $n_{m,j}$ and count the deal as $n_{m,j}$ deals:

$$n_{m,i} = \left[ \frac{FeePCP_{m,j}}{MED_{FeePCP}} \right]$$

where the operator $[\cdot]$ means rounding to the nearest integer.

Figure 6: Advisory Fee and Deal Value

This figure illustrates the relation between the advisory fee (as a percent of deal value) and the logarithm of deal value. The x-axis is the logarithm of deal value and the y-axis is the advisory fee divided by deal value (fee percent). We group deals into 15 bins based on deal value and calculate the average logarithm of deal value and the average fee percent within each bin. Red hollow dots represent the fee paid by acquirers and gray solid dots represent the fee paid by targets. The straight lines are the lines of best fit using OLS regression in Equation 6.