

Human Capital Portability and Worker Career Choices: Evidence from M&A Bankers

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Abstract

We quantify the importance of firm-specific human capital in explaining workers' career choices. We develop a model that allows workers to accumulate both portable and non-portable human capital through their work experience and learn about their match quality with current employers over time. We also allow bankers to choose between firms that offer different levels of portability and production efficiency. The model is estimated to match banker career data in the M&A advisory industry, which is populated by bulge bracket and boutique firms. Our estimation suggests that bankers in boutique firms accumulate less portable human capital but enjoy higher efficiency. Such a trade-off 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. We also gauge the extent to which non-portable human capital affects labor allocation and shapes industry structure.

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

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1 Introduction

Firm-specific human capital is a key determinant of worker mobility (Becker, 1962; Parsons, 1972; Lazear, 2009), which in turn shapes firm boundaries and growth (Zingales, 2000; Marx et al., 2009; Berk et al., 2010). 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. The portability of human capital is particularly relevant for highly skilled workers, whose jobs require frequent interaction with colleagues and clients (e.g., Topel 1991, Connolly and Gottschalk 2006, Custódio et al. 2013, and Brown and Matsa 2016). Despite its importance, less is known regarding how much of workers’ human capital is non-portable, how portability varies across firms, and to what extent it affects worker career choices.

This study quantifies the portability of human capital across firms and its effects on workers. We build a dynamic model that endogenizes workers’ career choices and human capital buildup. We then estimate model parameters to match granular data on investment bankers’ career paths in the M&A advisory industry. Our estimation shows that a substantial portion of bankers’ human capital is not portable across firms, despite that those firms perform highly similar tasks. This suggests that the non-portable human capital is firm-specific and not task-specific (Gathmann and Schönberg, 2010). Moreover, portability varies significantly across firms. It is lower for workers in small, focused firms than for those working in large, diversified firms. Facing job opportunities from both types of firms, workers optimize over human capital portability and efficiency to make career decisions.

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. Second, bankers perform similar tasks across all firms. Their output can be measured based on the deals they advise. 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. More importantly, the M&A

advisory industry consists of two types of firms adopting distinct business models: bulge bracket banks and boutique banks. Bulge bracket banks are large, diversified firms that offer a full range of investment banking products and serve a broad client base. Boutique banks are small, focus on advising M&A deals, and advocate individual attention to a select group of clients. The breadth of bankers’ network and skills can thus vary across these two sectors. In addition, boutique firms bear lower overhead costs and can distribute more profit to their employees. They are often considered to have more efficient operations.¹

The model embeds realistic features of the industry. It contains two sectors, diversified (bulge bracket) and focused (boutique) sectors, with homogeneous firms in each sector. Within each firm, bankers generate and advise deals. When advising a deal, they accumulate both general and firm-specific human capital (i.e., *learning-by-doing*, Nagypál 2007). We refer to the proportion of general human capital as “portability” and the proportion of firm-specific skills as “non-portability.” Both firms and bankers aim to maximize joint profit, determined by efficiency and the number of deals generated. The model allows portability and efficiency to vary across sectors, but imposes no priors on the relative level of these parameters.

Deal volume is a key metric of banker performance. It is determined by a banker’s human capital and his match quality with the employer (i.e., an advisory firm). A high match quality means that the banker has a strong synergy with the firm and can generate more deals. The banker does not observe match quality but can learn about it over time based on past deal volume (i.e., *learning about match quality*, Jovanovic 1979). In each period, he faces the following career choices: staying with the current firm, switching to another firm 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

¹Anecdotal evidence suggests that in boutique firms, workers can acquire specialized skills and receive a larger share of the deal profit. See, for example, <https://www.wallstreeoasis.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 boutique firms also separates us from discussions on the relation between financially constrained firms and human capital investment (Becker, 1962; Popov, 2014).

during the transition. When choosing between the two sectors, the banker accounts for both efficiency and human capital portability in those sectors.

To compare model predictions with actual empirical patterns, we construct a novel dataset on investment bankers' employment history and the M&A deals they advise. Information 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 trace his career path using the BrokerCheck Report prepared by the Financial Industry Regulatory Authority (FINRA). Combining these two databases, we assemble a large sample of investment bankers' career trajectories. 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 every point in time.

Matching moments generated by the model to those in the data, we are able to estimate and quantify several important parameters, including the human capital portability and the efficiency of both sectors, as well as the cross-sectional distribution of match quality. Estimating the comprehensive model, we are able to identify human capital portability through the change in banker performance around job transitions. This is because bankers that possess more non-portable human capital should suffer a bigger performance decline during transitions. Yet empirically, the observed performance change is confounded by an endogenous selection effect: bankers who consider themselves poorly matched with their current firms are more likely to change jobs in seek of a higher match quality with the next employer. We endogenize the selection effect in the model and isolate the loss of non-portable human capital in our estimation.

Our estimation suggests that human capital portability is substantially lower for boutique firms than for bulge bracket firms: Of the human capital gained by bankers from a bulge bracket firm, 85% is portable. This fraction drops to 60% for a boutique firm. In the meanwhile, boutique firms are 3% more efficient than their bulge bracket counterparts. In other words, boutique banks generate 3% higher profit than bulge bracket banks with every unit of human capital.

With these estimates, we present 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 leaving a boutique firm leads to steeper human capital losses. As a result, boutique firm employees are willing to tolerate worse match quality, as evidenced by more severe under-performance before job separation. Second, bankers' preferences between bulge bracket and boutique firms change 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 evaluate the effect of human capital non-portability (i.e., portability friction) and the uncertainty regarding match quality (i.e., information friction). To this end, we consider three counterfactual scenarios: (1) perfect portability, where workers only accumulate portable 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. Our experiments suggest that these frictions generate profound influence on workers' mobility and value. For example, employment value increases by 5.5% and 8.5% when we eliminate the portability friction and information friction, respectively. It increases by 11.3% when neither friction is present. Moreover, these labor market frictions generate heterogeneous effects on bankers at different career stages, affecting most strongly bankers at the middle of their careers. This is because middle-career bankers derive a high expected value from being in a well-matched firm. They also possess a substantial amount of firm-specific human capital. Knowing the true match quality can help them make accurate and timely decisions to switch jobs. Having fully portable human capital makes such job transitions costless.

We next test whether our framework can account for other sources of variation in human capital portability. Specifically, we consider that portability can vary across indi-

viduals based on how closely they work with a team. People that work in teams build up skills and knowledge specific to the team. When they change jobs, they lose such synergy and may suffer from a stronger performance decline than those that work alone (Silva et al. (2020)). We extend the model to account for such heterogeneity across bankers. Our model fits the data well and can explain the large performance gap around job transitions between bankers that frequently co-advise deals with colleagues and bankers that do not.

Finally, we show that human capital portability influences industry structure. With a human capital portability gap between the two sectors being 22%, our baseline model matches the growth in boutique banks' market share from 10% to 48% in the past two decades. We then counterfactually change the portability gap and simulate banker migration across the two sectors. If the portability gap decreases by 50%, boutique banks would have captured 81% of the market share over the past two decades. If the gap increases by 50%, there would have been little expansion of the boutique sector. This analysis suggests that the variation of human capital portability across firms plays a pivotal role in defining firm boundaries and shaping industry structure.

In closing, we provide two caveats regarding our framework. First, our model abstracts from discussing wages or compensation contracts by assuming frictionless bargaining. Under this assumption, the banker and the firm split the surplus in a way that the banker is compensated on par with his outside option at any time plus a share of the surplus. They stay matched as long as doing so generates positive joint surplus, and the banker's optimal career decisions maximize the joint surplus. Our setting is also consistent with an alternative environment where there is no bargaining and the firm simply offers the banker a fixed share of 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. A long-standing literature predicts that firm-specific human capital plays an important role in determining labor market outcomes (see, e.g., [Becker 1962](#), [Jovanovic 1979](#), [Jacobson et al. 1993](#), and [Acemoglu and Pischke 1999](#)). Recent empirical work has focused on showing the existence of firm-specific human capital or measuring the portability of skills across tasks.² Our study is the first to quantify the buildup of firm-specific human capital. Our structural approach allows us to track how the portability of human capital changes over workers' life cycle and across firms, which also 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 focus mainly on physical capital allocation and examine how various frictions generate distortions on the flow of capital ([Maksimovic and Phillips, 2001](#); [Yang, 2008](#); [Warusawitharana, 2008](#); [Bertola and Caballero, 1994](#); [Lanteri, 2018](#); [Li and Whited, 2015](#)). We relate to this literature by studying the allocation of human capital. We document that the lack of portability in firm-specific knowledge represents a key friction that distorts human capital allocation. In this regard, our paper is also related to [Sun and Xiaolan \(2019\)](#), who study the effect of firms' intangible capital portability. In particular, the fact that intangible capital is embodied in firms' employees significantly influences how firms finance intangible investments and their capital structure. Our study complements [Sun and Xiaolan \(2019\)](#) by focusing on workers' employment choices. We also use micro-level data to measure the extent to which the non-portability of human capital influences productivity and the structure of the M&A advisory industry.

²For example, [Groysberg et al. \(2006\)](#) discuss the portability of leadership skills. [Gathmann and Schönberg \(2010\)](#) separately measure the portability of skills across firms and across tasks. [Huckman and Pisano \(2006\)](#) look at the portability of skills for cardiac surgeons across hospital. [Groysberg et al. \(2008\)](#) show that star security analysts suffer a decline in performance once they move across firms.

2 Model

2.1 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 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 ω .

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.³ 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:

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

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.

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

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:

$$\pi_{i,b,t} = \lambda_s \cdot n_{i,b,t} \quad (3)$$

where s denotes the sector, with $s = 0$ indicating bulge bracket banks and $s = 1$ indicating boutique banks; λ_s captures sector-specific efficiency: when λ_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.

A banker builds up human capital by advising deals (i.e., learning-by-doing). Without

³While 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.

considering a job switch, banker human capital evolves following the law of motion below:

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

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

where $1 - \rho$ controls the fraction of old human capital that becomes obsolete and $\ell(\cdot)$ determines the speed of learning-by-doing.⁴ The parameter $\delta_s \in [0, 1]$ indicates the proportion of human capital acquired through each deal that is firm-specific: when δ_s is high, a larger fraction of human capital accumulates to its non-portable component. δ_s varies across sectors.

Overall, there are two key parameters differentiating between the bulge bracket and boutique sectors: efficiency (λ_s) and human capital specificity (δ_s). Such cross-sectoral differences suggest that bankers working for boutique firms may accumulate firm-specific human capital at a different speed from bankers working for bulge bracket firms. Boutique and bulge bracket banks may also utilize their employees' human capital differently, thus generating different profits from every unit of human capital. 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

⁴If $\ell(x)$ is a positive 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.”

updates his perception to $p_{i,b,t+1}$ based on the 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 are 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, ω, p) .

2.2 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.⁵ 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 η that the banker exits the industry and loses all his continuation value.

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

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

⁵This 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.

where

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

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

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 χ 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, ω , is lost during the job switch. Upon the job switch, the banker's perceived match quality with the new employer resets to the prior distribution.

We note that the assumption that bankers obtain χ fraction of the total surplus is consistent with a Nash Bargaining framework. 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 (e.g., Diamond 1982, Mortensen 1982, and Moscarini 2005). χ is not used to match wage data when we estimate the model. Its value thus bears no consequences for our estimation results.

2.3 Model mechanism

As discussed in Section 2.1, the two sectors (bulge bracket and boutique) differ in two dimensions: efficiency, captured by the parameter λ_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 porta-

bility determines the sorting of bankers into the two sectors. We present the full model solution in Section 2.4. 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 ω . We make the following additional assumptions to facilitate our analysis in the simplified model:

1. The match quality μ is 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:

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

where $\bar{h} = \frac{b\ell}{1 - (\rho + a\ell)}$ 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 $V_s(\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b)$.

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

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

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

$$V_s(h) \approx \lambda_s (A_0 + A_1(1 - \delta_s) + A_2h) \quad (11)$$

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 λ_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 λ_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.

This simplified model helps illustrate the intuition behind workers’ tradeoff between efficiency and portability in making career choices. In the next section, we solve the full model, which embeds more realistic features such as workers learning about match quality and switching jobs between the boutique and bulge bracket sectors.

2.4 Model Solution

To solve the full model, we return to the setting laid out in Sections 2.1 and 2.2. 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.⁶ To illustrate the mechanism, we focus on bankers who have not switched jobs

⁶Parameter estimates are reported in Table 3, and we defer the discussion of them to the next section.

previously, so that their portable human capital h , and non-portable human capital, ω , 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, switching jobs as soon as the perceived match quality drops below a cutoff. The cutoff value, however, differs across 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 of these bankers. Our estimates in Section 3 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:

$$\gamma = \frac{\frac{dU}{dh} - \frac{dU}{d\omega}}{\frac{dU}{dh}}, \quad (13)$$

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.

3 Estimation

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

3.1 Data and Sample Construction

We collect the identity and deal-making history of investment bankers from the MergerMarket database. MergerMarket records M&A deals worldwide with a transaction value over \$5 million conducted during the period of 2000 through 2018. 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, the advisory bank, the announcement and completion dates of the deal, and the transaction value. The distinguishing feature of the database is that it provides the names of the investment bankers 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 Merrill 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 accumulate human capital as they work through deals. The more time and efforts they put into the deal, the more they learn from the process. Advisors’ time and efforts can be directly reflected by the amount of fees they receive. Accordingly, we measure bankers’ human capital buildup using fee-adjusted deal numbers, accounting for both the number of deals that bankers have advised in the past and the amount of fees they receive for each deal. [Appendix B](#) describes this measure in greater detail.

3.2 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 β to be 0.9, a value commonly used in the literature. We set the exogenous exit rate, η , 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, λ_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 ℓ 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; λ_1 , the efficiency of boutique banks relative to that of the bulge bracket sector; $\{a, b\}$, which control the slope and constant coefficients of the expected deal number specified in Equation 2; ℓ , the overall speed of learning-by-doing; α , which controls the declining marginal benefits of learning-by-doing; ρ , 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 λ and the portability parameter δ 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 λ_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 λ_0 to 1 for the bulge bracket sector. Larger values of λ_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 α , and the larger α is, the faster the marginal benefits decline. We run the following regression in both the model and data:

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

where y is the total years of working experience of the banker. If learning-by-doing has decreasing return to scale, we expect $\gamma_1 > 0$ and $\gamma_2 < 0$. The combination of the two parameters helps identify α .

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:

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

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 coefficients ϱ_1 and ϱ_3 to be low if bankers learn slowly and thus ℓ 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 ℓ .

The parameter ρ 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 ϱ_τ , to identify ρ . Intuitively, a smaller spread implies a higher value of ρ .

Last, we identify human capital specificity (non-portability) δ_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.

Figure 4 illustrates how the perceived match quality, human capital, and the number of deals advised by a banker evolve as the banker switches from one employee to another. The left panel shows the results for bulge bracket exodus and the left panel shows the results for boutique exodus. First, we note that the transitioning banker loses much human capital as he departs from the current bank (the red line with square markers), and the dip in human capital is particularly large if his current employer is a boutique bank, because a larger fraction of human capital built in a boutique bank is firm-specific. This reflects the portability effect. Meanwhile, the perceived match quality gradually declines prior to the job change and is then reset to the unconditional mean right after the transition (the purple line with plus markers). This happens because a banker is more likely to transition as his perceived match quality deteriorates, and once he joins a new bank, the match quality is redrawn. We also observe that the decline in perceived match quality, which triggers the job switch, is larger for the banker who worked for a boutique bank, because the losses in human capital as leaving a boutique bank are more substantial and thus the banker is more cautious on making the transition decision. Combining the selection effect and portability effect, we find that the deal number dips upon transition but quickly rebound for a banker who departs from a bulge bracket bank, but the deal number dives much deeper and recovers more slowly for a banker who departs from a

boutique bank (the blue line with circle markers).

To match these patterns in SMM, we measure the overall changes of deal number around transition as:

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

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 τ years after the transition.⁷ 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 all else constant, $\Delta n_{s,i,t}$ is more negative when δ_s is larger.

4 Empirical Results

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

4.1 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 only 1.87% of bankers move from a bulge bracket bank to another bulge bracket bank per year. 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%, respectively. In addition, the model predicts that the net labor flow into 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.

Both bankers' overall mobility and net flow into the boutique sector increase with their seniority. There are two reasons why our model predicts decreasing labor mobility. First, bankers learn about their match quality gradually over time and switch employers

⁷Note 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.

if they perceive the existing match as low. 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. Conditional on switching employment, more senior bankers have a higher probability of transiting into the boutique sector, which offers less portable human capital, but also allows the bankers to utilize their existing human capital more efficiently. In the model, the correlation between the overall labor mobility and bankers' seniority is -38.03%, and that between the net labor flow into the boutique sector and the banker seniority is -44.16%. These numbers match closely with their data counterparts (-43.50% and -48.57%) though they are not explicitly targeted in our moment matching process. 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.

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 ℓ and ρ .

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 marginal benefit from learning-by-doing declines 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 3.2, this change is driven by two counteracting forces. First, transitioning 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.

4.2 Parameter Estimates

Table 3 reports the parameter estimates. Panel A presents the calibrated parameters as discussed in Section 3.2. 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 λ_1 , the efficiency of boutique banks, to be 1.032. Given that the efficiency of bulge bracket banks, λ_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 λ_1 seems consistent with the documented 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 λ_0 lower than λ_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, ρ , 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.

4.3 Estimating Heterogeneity of Human Capital Portability

Estimation of our baseline model shows that human capital non-portability can vary widely across bank sectors. The cross-sectional variation we identify in our baseline estimation is driven mainly by the difference in scope and organizational structure of different types of institutions. In addition to the institution-side effects, heterogeneity in portability can also originate from the worker side— for example, some bankers may collaborate more with colleagues and thus tie closely to their existing teams, while others may act independently and therefore are more adaptive to a changing environment.

In this section, we reestimate our model to fit the heterogeneity in human capital portability originated from the worker side. The purpose of this exercise is two-fold. First, it puts our model to a more strenuous test by ascertaining that it can detect changes in human capital portability across subsamples of bankers while keeping a close match on other features of their career trajectory. Second, we use our estimation to quantify a key determinant of human capital portability—collaboration intensity with coworkers. The estimation results also help to illuminate the different patterns in productivity among job switchers and why the pattern depends not only on these switching employees' own career trajectory, but also how their career paths overlap with their major coworkers.

We start by constructing a proxy for the degree of collaboration at the advisor-bank level. More specifically, for each individual working in a bank, we count the total number of collaborations he has had with colleagues since he joined the bank to date. A collaboration is considered as a unique colleague who co-advises a deal with the banker

of interest, whereby colleagues refer to other bankers who are currently working in the same bank. If a banker works on two deals with the same colleague, we count it as two collaborations because these experiences strengthen the banker’s relationship with his colleague. The total number of collaborations is then normalized by the total number of people working in the bank so that we measure the average strength of a banker’s synergy and relationship with his colleagues. We refer to the resulting ratio as “collaboration intensity.” Collaboration intensity is specific to individual bankers at specific workplaces and hence cannot be passed on to their next employments. Higher collaboration intensity should reduce the portability of a banker’s human capital.

We test this conjecture by comparing the change in deal volume during job transitions between the high- and low-collaboration intensity groups. The change in deal volume is defined as the difference in the number of deals generated by a banker during the future three years and the past three years ($\Delta n_{i,t}$). We run the following regression:

$$\begin{aligned} \Delta n_{i,t} = & \beta_1 Exit_{i,b,b',t} \times High\ Collaboration\ Intensity \\ & + \beta_2 Exit_{i,b,b',t} + \alpha_{b,h} + \alpha_{b',h} + \tau_{t,h} + \epsilon_{i,t}, \end{aligned}$$

where $Exit_{i,b,b',t}$ is an indicator for whether banker i moves from firm b to firm b' during year t , and $High\ Collaboration\ Intensity$ is an indicator for whether banker i has collaborated with colleagues in firm b more than the median banker within his tenure range. We control for interactive fixed effects between the current employer, the future employer, and year with the type of collaboration intensity. These stringent fixed effects help remove the sorting of banker collaboration across bank and over time. We are interested in β_1 that indicates the relative drop in performance between bankers that frequently collaborate with colleagues and bankers that do not.

Table 5 reports the results from this analysis. The estimated β_1 is significantly negative, suggesting that bankers sharing a strong tie with their colleagues suffer a steeper post-transition performance decline of around -0.17 compared to other bankers. This effect is consistent with the argument that relationship with colleagues contributes to the

non-portability of human capital.

To fit these observed data features, we extend our baseline model by embedding two groups of bankers within each sector—“high collaboration intensity” group who have more cooperative projects and stronger workplace relationship with co-workers, and “low collaboration intensity” group who work more independently. We introduce a new parameter, σ , to capture the heterogeneity of human capital portability across the two groups. Specifically, for “low collaboration intensity” bankers, we assume that the fraction of portable human capital they build up is $(1 - \delta_b)(1 + \sigma)$. In contrast, bankers with “high collaboration intensity” have less human capital, so we assume this fraction to be $(1 - \delta_b)(1 - \sigma)$. In this extended model, a banker’s total human capital portability is determined by two factors— his employer’s sector and his collaboration intensity.

Our extended model generates additional predictions regarding the differential patterns around job transitions for bankers with different collaboration intensities. When $\sigma = 0$, the two groups exhibit the same pattern surrounding job transitions; when σ increases, as illustrated in Figure 5, bankers in the high-collaboration intensity group (left panel) experience a larger decline in deal number when they switch employers, compared with bankers from the low-collaboration intensity group (right panel), with the gap being controlled by the parameter, σ . Hence the differential pattern across the two groups can effectively identify σ .

We define the differential across groups as:

$$D\Delta = E[\Delta n_{L,i,t} - \Delta n_{H,i,t}], \quad (17)$$

where $\Delta n_{g,i,t}$ is the change in deal number in a $[-3, 3]$ year window surrounding the job transition year t for banker i (as defined in Equation 16), with the subscript $g \in \{H, L\}$ denoting the high- or low-collaboration intensity group the banker belongs to. $D\Delta$ therefore captures the differential in average deal number change around job transitions between the two groups.

We estimate the extended model by matching $D\Delta$ and the 11 moments reported in Table 2. We present the parameter estimates and the model fit in Table 4. Panel A shows

that our model is able to closely match all targeted moments. In particular, it is able to capture the large gap between the deal number change around job transition for bankers with high- and low-collaboration intensities. In the model, as in the data, bankers who had intensive collaborations with their co-workers tend to suffer a larger decline in the number of deals they would advise in subsequent years when they switch employers.

Panel B reports the parameter estimates for the extended model. The parameter σ is estimated to be 0.142, implying a 30% gap in human capital portability between the two groups of bankers partitioned based on our empirical measure of collaboration intensity. By isolating the effect of σ , our model highlights the driving forces that underlies the differential pattern in deal numbers among switching bankers as documented in Table 5. For bankers who collaborate more with their colleagues and thus tie closely to their existing teams, job transition can be more costly as a larger fraction of their human capital accumulated on their original employment will be lost in the transition process. Meanwhile, other than σ (which is introduced only in the extended model), all parameter values remain fairly close to their estimates in the baseline model. The results also confirm that our baseline estimates of human capital portability across different bank sectors (bulge bracket vs. boutique) remain robust to including additional heterogeneity specific to each advisor-bank match.

5 Counterfactual Analyses

In this section, we examine how human capital portability and its heterogeneity across sectors influence individual bankers and the structure of the M&A advisory industry. We perform two sets of counterfactual experiments. The first analysis quantifies the effects of non-portable human capital on worker career and performance. It also compares the effects of non-portability to the effects of match-quality uncertainty. The second experiment examines how non-portable human capital affects the composition of the M&A advisory industry. We show that the effects we identify at the banker level does not wash out in aggregate, but instead lead to shifts in the industry structure.

5.1 Human Capital Non-portability, Match Quality, and Banker Career Outcomes

We quantify the extent to which unobservable match quality and nonportable human capital shape 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 sheds light on the efficiency improvement from providing additional signals regarding match quality to 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 6. First, we consider a scenario in which human capital is perfectly portable and we label it as “perfect portability” (i.e., PP). In this scenario, bankers suffer no human capital loss upon job transition. In the second scenario, we shut down information frictions and assume that match quality is immediately observable upon employment. We label this scenario as “perfect information” (i.e., PI). In the third scenario, bankers observe the match quality when they start their jobs and job transitions are costless. We label this scenario as “perfect portability and information” (i.e., PPI). We then compare four key variables in each of the three counterfactual models to their counterparts in the baseline model. These variables are labor mobility rate, the fraction of good matches, total human capital, and employment value. Labor mobility rate is defined as the number of bankers who switch jobs divided by the total number of bankers in the model economy. The fraction of good match is defined as the number of employment pairs with high match quality divided by the total number of pairs in the model economy. Total human capital is the total amount of human capital possessed by individual bankers that includes both the portable and non-portable components. Employment value is the value of the employment pair as solved in Equation 7.

Table 6 presents the results for the counterfactual analyses. Column 1 shows the variable values in the baseline model. The remaining columns report the variable values in each of the counterfactual models and the difference in these variables between the counterfactual models and the baseline model (i.e., counterfactual – baseline). We find that human capital non-portability and information friction on match quality have opposite effects on labor mobility rate. With perfect portability, job changes become less costly for bankers and they explore outside options more frequently. This significantly increases labor mobility. With perfect information, bankers are fully informed about the current match quality and are able to make more accurate job separation decisions. Labor mobility drops as a result. The two opposing effects cancel out when we eliminate both frictions in the third counterfactual scenario, leaving the overall labor mobility rate almost unchanged.

The fraction of good match increases as we eliminate labor market frictions. The improvement is greater with perfect information than with perfect portability. This finding is intuitive: even if job separations are costless, it still takes bankers time to gradually learn about the match quality and therefore bad match can persist. This suggests that policies aimed at improving the speed of learning about match quality can potentially make the labor market more efficient. We also find that the total human capital and employment value increase as we eliminate labor market frictions. In particular, if human capital is fully portable, employment value rises by about 5.5%, and if match quality is perfectly observed upon a pair is formed, employment value increases by 8.5%. Eliminating both frictions improves efficiency by about 11.3%.

The findings above show the effects of these labor market frictions on an average banker. We next investigate whether the frictions have differential effects on bankers in different career stages. To do so, we partition bankers based on their career stages into 5-year intervals. Figure 6 compares the three counterfactual models with the baseline model. The x-axis represents the career stages, and the y-axis represents the difference between the counterfactual model and the baseline model.

The upper-left panel illustrates the changes in labor mobility as we move from the

baseline model to the counterfactual models. Labor mobility increases for bankers in all career stages in the PP model. The increase, however, is smaller for senior bankers because they are more likely to have found a good match already in the baseline model, so the incremental value of portability is lower. The perfect-information (PI) and the perfect-portability-information (PPI) models exhibit more intriguing effects. Relative to its levels in the baseline model, labor mobility is higher in PP and PPI models for the most junior bankers (with the career stage of 1-5 years) but becomes lower for more seasoned bankers. This is because perfect information allows bankers to learn about a bad match and switch jobs without further delay. Bankers can also find a good match and “settle down” sooner, thus exhibiting lower mobility in later stages.

Corresponding to our analysis above, the upper-right panel confirms that the fraction of good matches in the model economy greatly improves in the PI and PPI models. The improvement is most pronounced for junior bankers, because perfect information allows junior bankers to quickly learn about bad matches and leave those employers. For senior bankers, the incremental effect is smaller because those bankers have had time to learn about their match quality even with information frictions.

The lower-left panel illustrates how the two frictions affect bankers’ human capital accumulation. Results suggest that eliminating these frictions benefit mid-career bankers (11-25 years) the most. The hump-shaped relation arises because mid-career bankers suffer the most from portability and information frictions. Many of those bankers have started to realize that their employers are not a good match and hope to move. Yet, they have accumulated a substantial amount of firm-specific human capital, making job changes highly costly. Eliminating the information friction speeds up learning and the search for a better match. Perfect portability allows bankers to preserve all human capital and facilitates job transitions. Both are crucial to the human capital accumulation of mid-career bankers. In comparison, junior and senior bankers benefit less from eliminating these frictions. This is because junior bankers have little firm-specific human capital and therefore they have little to lose in job transitions. Senior bankers are more likely to have found a good match and have a lower desire to change jobs.

Lastly, the lower-right panel confirms that eliminating these frictions can greatly increase the value created and thus improves the efficiency. The effects are also hump-shaped, indicating that efficiency gains are the largest for bankers in the mid-career stages when the interaction between the two frictions is the strongest.

5.2 Industry Structure

Our previous analysis show that non-portable human capital influences individual bankers' career paths and creates a flexibility-efficiency tradeoff over their life cycles. Given these findings, it is important to also understand whether these effects persist in aggregate, and to what degree they shape the M&A advisory industry.

Over the past two decades, the M&A advisory industry has observed a notable rise of boutique banks (Gao et al., 2019). The labor share of boutique banks has increased from 10% in 2000 to almost 40% in most recent years. The prior literature focuses on the strength of boutique banks' organizational structures, yet less is known regarding the labor market frictions associated with boutique firms. Has the portability friction that we document constrained the growth of the boutique sector? We address this question through a counterfactual experiment, gauging the extent to which human capital non-portability shape the structure of the M&A advisory industry.

We vary the portability gap between the bulge bracket and boutique sectors (i.e, $\delta_1 - \delta_0$) and simulate bankers' choices between those sectors based on each value. The portability gap equals 32% (0.46-0.117) in the baseline model. In our counterfactual experiment, we change the value of δ_1 so that the portability gap can increase or decrease by 25% and 50%, respectively. We solve the model using the new δ_1 , while keeping all other parameters at their original values reported in Table 3. We then simulate bankers' career paths under these new model parametrizations for 20 years. Each simulation starts with 10% bankers being randomly assigned to the boutique sector. We track how the labor market share of the boutique sector evolves over time.

Figure 7 summarizes the results from the simulation analysis. The x-axis indicates the number of years that has 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. With a base level of the portability gap being 32%, the labor share of the boutique sector increases to 31% over 20 years. This matches the share of boutique bankers observed in the data. Note that we do not directly target any time series moments in our moment-matching process. Nevertheless, with the estimated parameters, our model can closely track the increasing presence of the boutique sector, which serves as a useful external validation to our model mechanism.

The expansion of the boutique sector slows down with a higher portability gap. The lack of human capital portability in the boutique sector makes it difficult to attract talents, especially in an environment with uncertain match quality. Bankers are more inclined to join the bulge bracket sector which offers more flexibility in case they face a bad match and need to change jobs in the future. The effect of human capital non-portability is not only qualitatively intuitive, but also quantitatively important. More specifically, boutique banks can hardly capture any market share if we increase the gap by 50%. If we reduce the portability gap by 50%, nearly 80% bankers would migrate to the boutique sector over the 20-year horizon. Overall, our results suggest that the sectoral heterogeneity of human capital portability is a key determinant of industry structure.

6 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 bracket 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 $H = h + \omega$. The color scales indicate labor mobility, with lighter color indicating higher mobility.

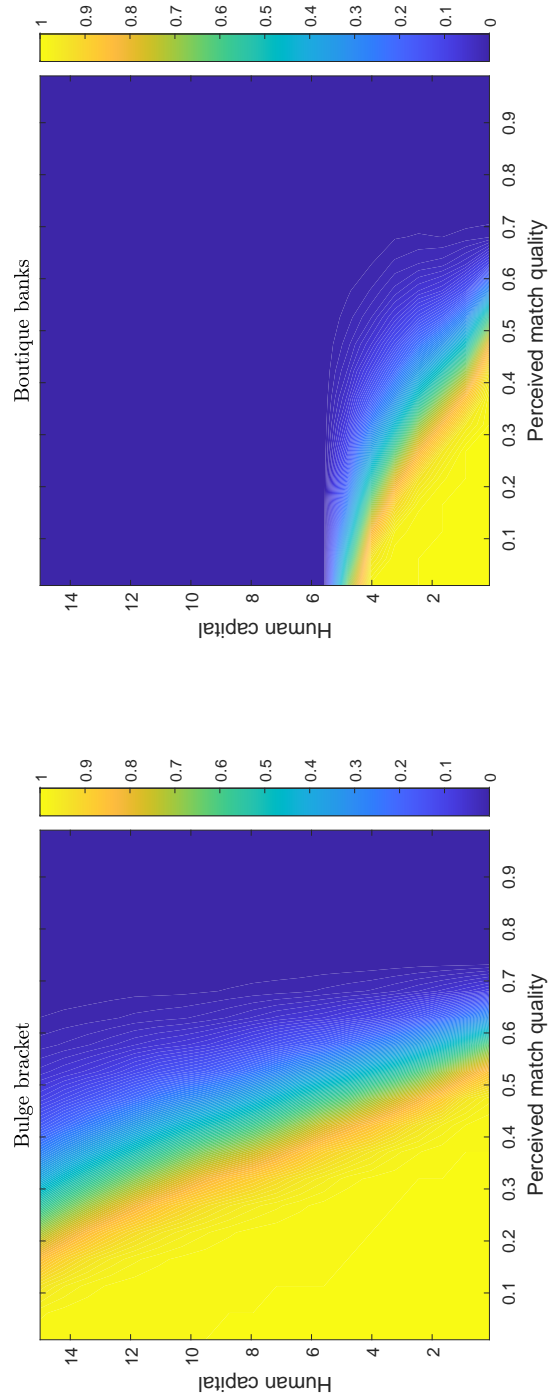


Figure 2. Portability Premium

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 equation 13. The left panel shows the results for the bulge bracket sector and the right panel shows the results for the boutique banks. 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.

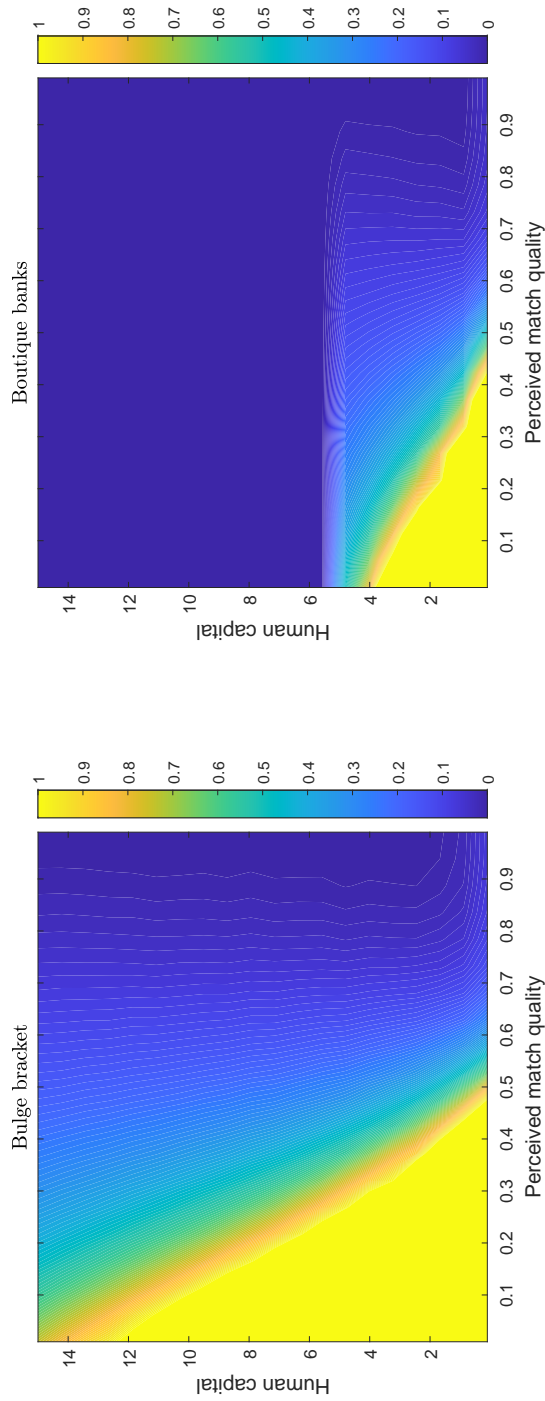


Figure 3. Sector Choices: Who Works for Whom?

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.

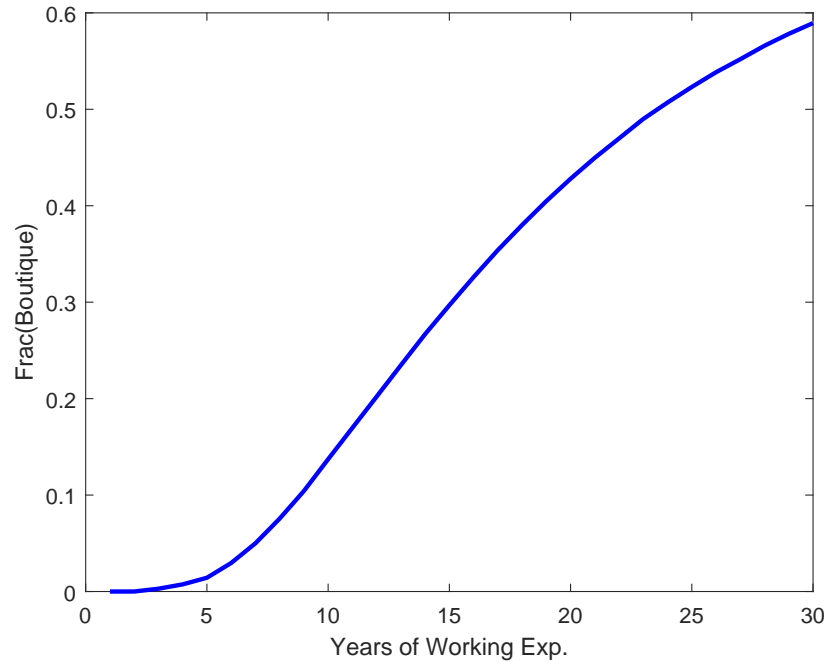


Figure 4. Changes Around Banker Transition

This figure shows the changes in human capital, perceived match quality, and the number of deals advised by a banker when the banker switches from one employee to another. The graphs are generated based on the parameters reported in Table 3. The left panel shows the results for bulge bracket exodus and the right panel shows the results for boutique exodus. The blue lines with circle markers plot the evolution of deal number, the red lines with square markers depicts the dynamics of human capital, and the purple line with the plus markers describes the fluctuation in perceived match quality. The event window is centered at the transition year $t = 0$. We normalize the human capital and deal number to be zero at year $t = -2$.

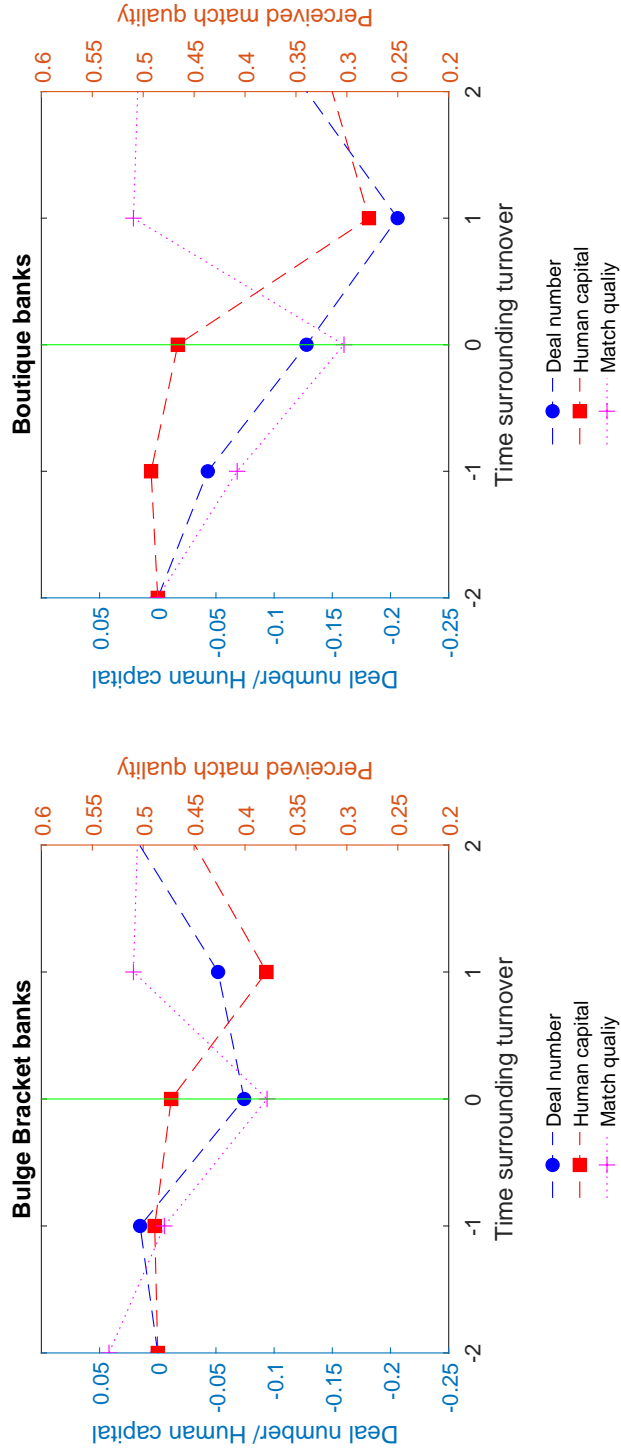


Figure 5. Collaboration Intensity and Job Transition

This figure shows the changes in human capital, perceived match quality, and the number of deals advised by a banker when the banker switches job. The left panel shows the results for bankers with high collaboration intensity and the right panel shows the results for bankers with low collaboration intensity. The blue lines with circle markers plot the evolution of deal number, the red lines with square markers depicts the dynamics of human capital, and the purple line with the plus markers describes the fluctuation in perceived match quality. The event window is centered at the transition year $t = 0$. We normalize the human capital and deal number to be zero at year $t = -2$. Parameters are set the values reported in Table 3.

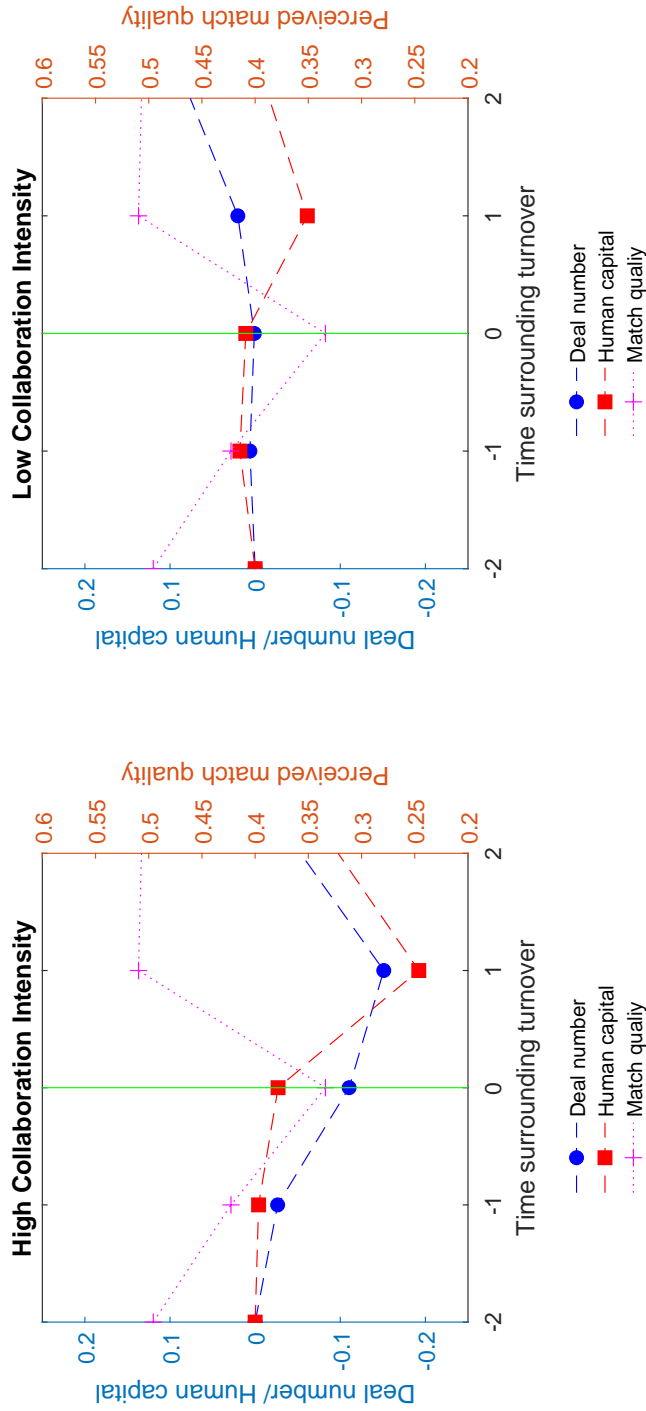


Figure 6. Counterfactual Analyses

This figure presents results from three counterfactual models: perfect-portability (PP), perfect-information (PI), and perfect-portability-information (PPI). We compare the predictions by these counterfactual models with those by the baseline model and plot the differences in bar charts. The upper-left panel shows the changes in labor mobility rate when we move from the baseline model to the counterfactual models, the upper-right panel shows the changes in the fraction of employment pairs with good match quality, the lower-left panel shows the changes in human capital, and the lower-right panel shows the changes in employment value. The blue bars represent the PP model, the orange bars represent the PI model, and the yellow bars represent the PPI model. Parameters are set to the values reported in Table 3.

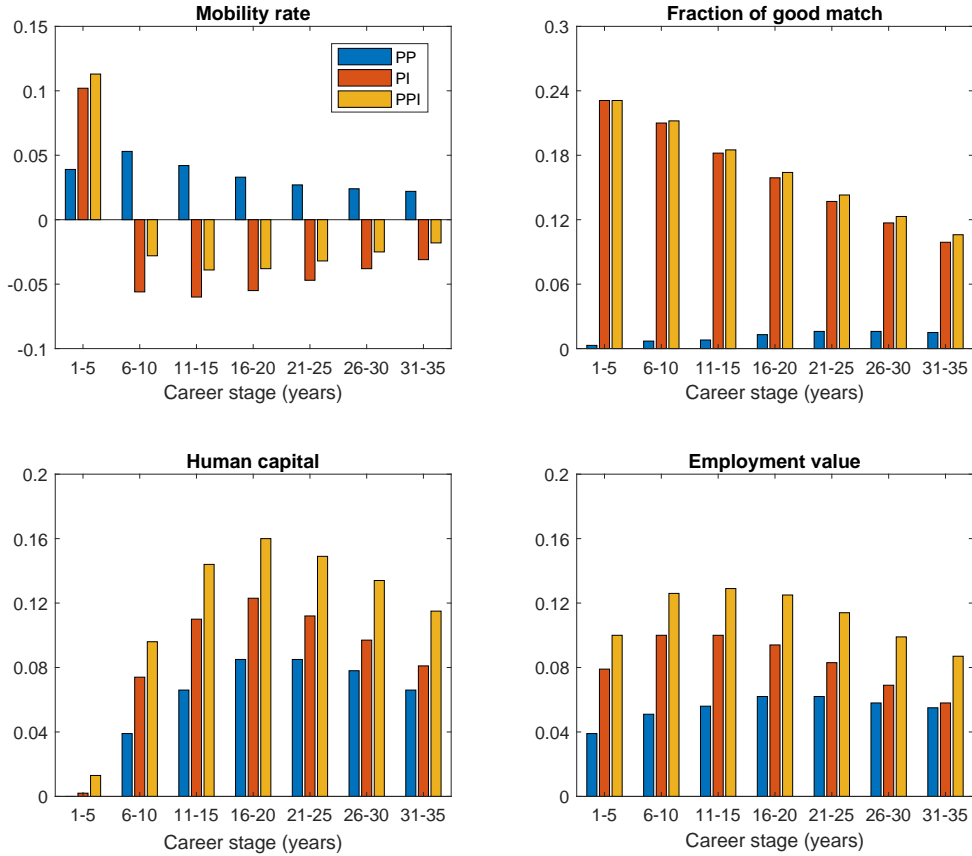


Figure 7. Human Capital Portability Gap and Boutique Bank Labor Share

This figure shows how the labor 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.

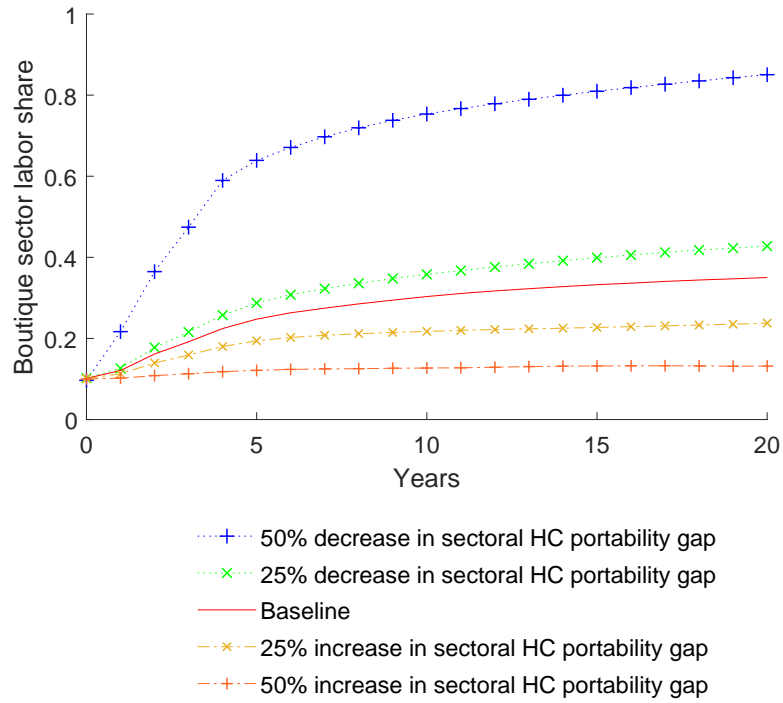


Table 1
Moment Construction and Variable Definition

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 bankers 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 ϱ_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 ϱ_3 in Equation 15
Avg. deal number per banker per year	The average number of deals generated by each banker in a given year
Loading of deal number on banker years of experience	Coefficient 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 γ_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 γ_2 in Equation 14
Avg. deal number per new entrant per year	The average number of deals generated by each new entrant in his/her first year as 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 table 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 divided 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	Empirical value	Simulated value	Standard error
Relocation rate within the bulge bracket sector	0.0187	0.0236	0.0028
Relocation rate within the boutique sector	0.0109	0.0104	0.0014
Net labor inflow into the boutique sector	0.0087	0.0121	0.0017
Loading of deal number on avg. past 1-2 yr deal number	0.1511	0.1598	0.0269
Loading of deal number on avg. past 3-4 yr deal number	0.0803	0.0640	0.0347
Avg. deal number per banker per year	0.8034	0.7992	0.0490
Loading of deal number on banker years of experience	0.1269	0.1208	0.0056
Loading of deal number on banker years of experience squared	-0.0026	-0.0029	0.0003
Avg. deal number per new entrant per year	0.2145	0.1979	0.0274
Deal num. chg. around banker transition from bulge bracket	0.0799	0.0644	0.0447
Deal num. chg. around banker transition from boutique	-0.1005	-0.1188	0.0549

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. β is the discount rate, η is the exogenous exit rate of bankers, λ_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 ℓ . q is the probability of having a good match, λ_1 is the efficiency of boutique banks, α 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, ℓ is the parameter that controls the overall speed of learning-by-doing in Equation 12, ρ is the persistence of human capital, and δ_0 and δ_1 are human capital portability in the bulge bracket and boutique sector, respectively.

Panel A. Calibrated/Normalized Parameters

	Calibration		Normalization	
	β	η	λ_0	c
Value	0.90	0.04	1	1

Panel B. Estimated Parameters

	q	λ_1	α	a	b	ℓ	ρ	δ_0	δ_1
Estimate	0.510	1.032	0.823	0.986	0.188	0.332	0.884	0.117	0.460
Standard errors	0.114	0.005	0.387	0.576	0.029	0.102	0.082	0.024	0.120

Table 4
Heterogeneity in Human Capital Portability

This table shows the model fit (Panel A) and the parameter estimates (Panel B) for the extended model that allows for heterogeneous human capital portability across bankers. The first 11 moments in SMM are the same as those in the baseline (reported in Table 2), and we add one additional moment, namely, the differential of deal number change around job transitions between the high- and low-portability groups (defined in equation 17), to identify the new parameter σ .

Panel A. Model Fit

Moment	Empirical value	Simulated value	Standard error
Relocation rate within the bulge bracket sector	0.0187	0.0275	0.0028
Relocation rate within the boutique sector	0.0109	0.0118	0.0014
Net labor inflow into the boutique sector	0.0087	0.0134	0.0017
Loading of deal number on avg. past 1-2 yr deal number	0.1511	0.1579	0.0269
Loading of deal number on avg. past 3-4 yr deal number	0.0803	0.0676	0.0347
Avg. deal number per banker per year	0.8034	0.7994	0.0490
Loading of deal number on banker years of experience	0.1269	0.1208	0.0056
Loading of deal number on banker years of experience squared	-0.0026	-0.0029	0.0003
Avg. deal number per new entrant per year	0.2145	0.1968	0.0274
Deal num. chg. around banker transition from bulge bracket	0.0799	0.1162	0.0447
Deal num. chg. around banker transition from boutique	-0.1005	-0.1039	0.0549
Diff. in deal num. chg. around banker transition btw. high- and low-portability group	-0.1744	-0.1668	0.0710

Panel B. Parameter Estimates

	Calibration						Normalization		
Value	β	η	λ_0	c			λ_0	c	
	0.90	0.04	1	1			1	1	
	q	λ_1	α	a	b	ℓ	ρ	δ_0	δ_1
Estimate	0.510	1.031	0.821	0.987	0.187	0.331	0.883	0.114	0.461
Standard errors	0.134	0.015	0.235	0.489	0.025	0.073	0.074	0.060	0.041
									σ
									0.142
									0.081

Table 5
Collaboration Intensity and Job Transition

This table shows changes in deal volume around banker job transitions when the banks has high or low collaboration intensity. The dependent variable is $\Delta n_{i,t}$, the difference in deal volume generated by a banker during the next three years and the past three years. *Exit* is an indicator for whether the banks switches jobs in a year. *High Collaboration Intensity* is an indicator for whether the banker's collaboration intensity ranks above the median in each tenure range. The sample includes all banker-years where the banker departs a bulge bracket bank or a boutique bank or the banker does not leave his job in a given year. Standard errors are clustered by people. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: $\Delta n_{i,t}$	(1)	(2)
Exit \times High Collaboration Intensity	-0.1744** (0.071)	-0.1629** (0.072)
Exit	Yes	Yes
Bank Sector \times High Collaboration Intensity FE	Yes	No
Bank \times High Collaboration Intensity FE	No	Yes
Next Bank Sector \times High Collaboration Intensity FE	Yes	Yes
Year \times High Collaboration Intensity FE	Yes	Yes
Observations	16,859	17,783
Adjusted R^2	0.074	0.086

Table 6
Frictions and Counterfactual Analyses

This table presents the results for the baseline model and three counterfactual scenarios in which we eliminate frictions in the labor market. “Perfect Portability” (PP) corresponds to a case where human capital is assumed to be fully portable (no portability friction); “Perfect Info” (PI) corresponds to a case where the match quality is assumed to be perfectly revealed upon the formation of each match (no information friction); “Perfect Portability and Information” (PPI) is a case where 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); we report both the raw levels of the variables (*level*) and the difference between the counterfactual scenarios and the baseline model (*change*).

	Baseline	Perfect Portability		Perfect Info		Perfect Port and Info	
	level	level	change	level	change	level	change
Boutique labor share	0.291	1.000	0.709	0.135	-0.156	0.491	0.200
Labor mobility rate	0.077	0.114	0.037	0.064	-0.013	0.080	0.003
Fraction of good match	0.618	0.627	0.009	0.791	0.173	0.796	0.178
Total human capital	1.319	1.373	0.054	1.398	0.079	1.427	0.108
Annual number of deals	0.933	0.963	0.030	1.043	0.110	1.059	0.127
Employment Value	0.997	1.051	0.054	1.083	0.085	1.111	0.113

Appendix 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:

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

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:

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

where

$$\begin{aligned} \phi &= \rho + a\ell \\ \bar{h} &= \frac{\ell b}{1 - (\rho + a\ell)} \end{aligned}$$

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:

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

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 $V_s(\rho \cdot h + (1 - \delta_s) \cdot \ell \cdot b)$.

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

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

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 $V_s(h)$:

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

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 substitute them into Equation A.6 and solve for the coefficients:

$$B_1 = \frac{a \cdot q \cdot \lambda_s}{(1 - \rho\beta(1 - q))(1 - \beta(\rho + a\ell))}$$

$$B_0 = \frac{\lambda_s}{1 - \beta(1 - q)} \left[b + \beta q \left(\frac{a\bar{h} + b}{1 - \beta} + \frac{abl - a\bar{h}}{1 - \beta(\rho + a\ell)} \right) + \frac{\beta(1 - q)b\ell a q(1 - \delta_s)}{(1 - \rho\beta(1 - q))(1 - \beta(\rho + a\ell))} \right]$$

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

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

where

$$A_0 = \frac{1}{1 - \beta(1 - q)} \left[b + \beta q \left(\frac{a\bar{h} + b}{1 - \beta} + \frac{abl - a\bar{h}}{1 - \beta(\rho + a\ell)} \right) \right] \quad (\text{A.8})$$

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

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

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

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

and thus $A_0 > 0$ holds as well.

Appendix 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 A.1. 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:

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

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 B.1 and the deal value observed in deals with missing fee data, we calculate a predicted advisory fee for these deals:

$$\begin{aligned} Fee\hat{Pct}_{m,i} &= a_m + b_m \cdot \ln(DealVal_i) \\ \hat{Fee}_{m,i} &= Fee\hat{Pct}_{m,i} \cdot DealVal_i \end{aligned}$$

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:

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

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:

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

where the operator $\lceil \cdot \rceil$ means rounding to the nearest integer.

Figure A.1. 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 B.1.

