Ownership Network and Job Mobility*

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Abstract

This paper examines how common ownership among employers affects both the quantity and quality of employee job mobility. I develop a model that motivates how overlapping ownership weakens labor competition and reduce job transitions, particularly toward high-quality employers. I then test these predictions using a large collection of résumé data from U.S. college graduates and exploiting the merger of two large institutional investors, which significantly changed overlapping ownership among S&P 500 companies. I find that a 1% increase in ownership similarity between two firms reduces job mobility between them by 4.3%. Furthermore, by analyzing the composition of job transitions, I show that overlapping ownership distorts labor market mobility by disproportionately reducing job transitions during the early career stage and toward larger and more productive employers.

JEL Classifications: G34, J42, K21, M50
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1 Introduction

Job mobility across firms is a key source of career development and wage growth, especially for young and highly skilled employees (Topel and Ward, 1992; Wachter and Bender, 2006; Starr et al., 2021; He and Wintoki, 2023; Deming, 2023). At the same time, high levels of talent turnover can result in substantial costs for employers (Oi, 1996; Haslag et al., 2022; Carvalho, 2023). These costs may lead firms to engage in collusive practices, such as refraining from competing for one another's employees, in order to restrict employees' outside options and lower their chances of departure (Ashenfelter et al., 2022; Gibson, 2024; Callaci et al., 2024; Ferrés et al., 2022; Begley et al., 2024; Herrera-Caicedo et al., 2024; Sharma, 2024).

Although such anticompetitive behavior by firms is illegal under Section 1 of the Sherman Act, antitrust efforts have historically focused on product markets. While there is growing attention toward potential antitrust issues in labor markets (DOJ and FTC, 2016; CEA, 2016; DOJ and FTC, 2023), the underlying factors and conditions that enable firms to coordinate in the labor market remain largely understudied.

In this paper, I examine how ownership similarity among employers influences the job mobility of their college-educated employees. Over the past few decades, the ownership structure of publicly traded firms in the U.S. has undergone a dramatic transformation, shifting from small retail investors to dominant financial institutions. Institutional ownership has risen from less than 10% in the 1950s to around 70% in 2010s (Blume and Keim, 2012; Azar et al., 2018; Ben-David et al., 2021) with the three largest asset managers – BlackRock, Vanguard, and State Street – collectively serving as the largest shareholders in nine out of ten S&P 500 firms, which together employ nearly one-third of the U.S. workforce(Goshen and Levit, 2022; Fichtner et al., 2017). That raises concerns about the potential impact of growing overlapping ownership among major U.S. corporations on employers' labor market power and employees' labor market outcomes (Bivens and Mishel, 2015; Steinbaum, 2021; Azar and Vives, 2021; Goshen and Levit, 2022).

This paper provides both theoretical and empirical evidence on how overlapping ownership among employers can adversely affect workers by reducing job mobility across firms. I begin by developing a simple model that clarifies how common ownership weakens competition for labor and depresses both the quantity and the quality of job mobility. The model is a repeated game in which firms decide whether to poach each other's workers, and the probability of successful poaching depends on their relative positions on a job ladder, with higher-quality employers having a greater likelihood of attracting workers. This asymmetry

in poaching success makes collusion particularly difficult to sustain between firms that differ substantially in quality.

The model further illustrates that the presence of common ownership increases the scope for tacit collusion by weakening firms' incentives to compete aggressively for talent. As a result, overlapping ownership restricts workers' outside options and reduces mobility between firms. Moreover, common ownership disproportionately facilitates collusion across firms that are far apart on the job ladder, making it harder for workers to move to substantially better employers and thereby limiting upward mobility.

I then test these hypotheses empirically by analyzing the job mobility of highly skilled workers in the U.S., drawing on a large collection of résumés from 21 million college graduates between 1995 to 2019. This dataset allows me to track job transitions across S&P 500 firms, which are the primary focus of my study.

To draw a casual link, I exploit the plausibly exogenous variation in ownership similarity of S&P 500 companies caused by BlackRock's acquisition of Barclays Global Investors (BGI) in 2009. The merger led BlackRock to become the largest shareholder in 34.8% of S&P 500 companies and increased their average ownership similarity by 4.4%.[1]

I employ a difference-in-differences identification strategy, using only variation in ownership similarity implied by the hypothetical combination of the two companies' portfolios at the end of 2008 prior to the merger announcement. Leveraging this approach, I show that firm-pairs in the top tertile of predicted increases in ownership similarity experienced, on average, 11% ($e^{-0.116} - 1$) lower employee flows between them after the merger compared to other firms.

Additionally, I use the implied impact of the merger as an instrument for the change in ownership similarity between firm-pairs before and after the merger. This approach enables me to quantitatively estimate the effect of employers' ownership similarity on employees' job mobility. My estimates indicate that 1% increase in ownership similarity between two firms reduces job mobility between them by 4.3% ($e^{-.044} - 1$).

[1]The change in average ownership similarity is computed by dividing the predicted change in ownership similarity induced by the merger by the initial ownership similarity in the last quarter of 2008. For more details on predicted change in ownership similarity, see $\Delta\chi_{fg}$ in Equation 8.

Next, I examine how common ownership among employers affects the composition of job transitions across different stages of a worker's career. Using variation across cohorts of U.S. bachelor's degree graduates who moved between S&P 500 firms from 2006 to 2015, I show that job mobility is highest around the time of graduation and declines steadily thereafter. I classify transitions into three career stages: the graduation year and before, early career (the first ten years after graduation), and late career (more than ten years after graduation). I find that greater ownership similarity reduces the share of job transitions in the early career stage by 2.3%, a decline that is largely offset by an increase in late-career mobility.

I further examine how this adverse effect on early-career job transitions varies across employer and employee characteristics. A large body of research shows that firms play a central role in shaping labour market outcomes (Card et al., 2013; Goldschmidt and Schmieder, 2017; Card et al., 2018; Sorkin, 2018; Abowd et al., 2018; Bonhomme et al., 2019). In particular, prior studies emphasise that both firm size and productivity are key determinants of wage growth and career development, especially early in workers' careers (Moore, 1911; Brown and Medoff, 1989; Oi and Idson, 1999; Bagger et al., 2014; Bloom et al., 2018; Colonnelli et al., 2018; Bartolucci et al., 2018; Haltiwanger et al., 2018; Arellano-Bover, 2024; Lochner and Schulz, 2024). Building on this literature, I examine how common ownership among employers affects early career transition into large and productive firms. Using firm-level financial data from Compustat, I construct measures of firm size (number of employees) and total factor productivity (TFP), where TFP is estimated using the control function approach developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). These measures allow me to compare origin and destination firms for each job transition and show that the negative effect of higher ownership similarity on early-career mobility is particularly pronounced among company pairs in the upper tertiles of the destination-to-origin ratios for firm size and productivity. This pattern suggests that common ownership disproportionately reduce workers' upward mobility toward significantly larger and more productive employers during the early stages of their careers.

Furthermore, I examine whether these mobility frictions vary by individual characteristics. I shows that the negative effect of ownership similarity is more pronounced for certain groups, particularly, STEM graduates, and individuals from top-ranked universities. These findings suggest that employers' common ownership may constrain upward job mobility, especially for workers with greater potential to access higher-quality employers, and may thus distort the efficient allocation of talent in the labor market.

This paper builds on two key strands of literature. First, it contributes to the growing body of research on the real effects of overlapping ownership. Prior studies have primarily focused on how common ownership influences product markets Azar et al., 2018; Newham et al., 2018; Backus et al., 2021; Ederer and Pellegrino, 2021, corporate investment (Gutiérrez and Philippon, 2016, 2018), innovation (López and Vives, 2019; Antón et al., 2024), and managerial compensation (Antón et al., 2023). The most closely related work to my paper is Azar et al. (2021), which uses administrative data from the U.S. Census Bureau to examine the impact of common ownership on employee wages. They exploit changes in overlapping ownership driven by firms' additions to the S&P 500 index as a shock to local competitors' ownership structures. They attribute the observed wage effects to increased employer market power and wage markdowns. In contrast, my paper employs a different identification strategy based on the merger of two large institutional investors. I also leverage a unique dataset of employee résumés, which enables me to precisely track changes in ownership similarity and job transitions between firms. The primary contribution of this paper is to provide evidence that employers' overlapping ownership can facilitate anti-competitive behavior, specifically by restricting employees' outside options and reducing labor mobility. Moreover, this paper offers novel insights into how ownership similarity between employers can distort labor market mobility by disproportionately reducing job transitions during the early career stage and toward large and productive employers.

In this regard, my paper also contributes to the second strand of literature, which includes recent studies providing empirical evidence on the causes and consequences of anti-poaching agreements between firms. Notably, Gibson (2024) and Ferrés et al. (2022) examine anti-poaching agreements in Silicon Valley during the mid-2000s, finding that such collusion reduces wages and non-wage benefits. Meanwhile, Begley et al. (2024) and Herrera-Caicedo et al. (2024) investigate how firms with shared board directors or executives are more likely to engage in these forms of collusive behavior.

The rest of the paper is organized as follows: Section 2 introduces a simple model of labor market collusion in infinitely repeated games. Section 3 describes the data, Section 4 outlines the estimation strategy, Section 5 presents the results, and Section 6 concludes.

2 A Model of labor market collusion in Infinitely Repeated Games

In this section, I provide a simple model of strategic interaction between employers that helps interpret the empirical analysis. I study a setting in which firms repeatedly decide whether to compete aggressively for each other's workers ("poach") or to refrain from such behavior ("not poach"). There are two key features in my model. Fist is that overlapping ownership across employers changes firms' incentives by inducing them to partially internalize rivals' payoffs. This channel can facilitate collusive outcomes and reduce worker mobility. Second the success of poaching and thus incentive for poaching depend on the position of poaching and target firms in the job ladder

Job ladder and asymmetric poaching probabilities

Consider two firms, f and g. Let p_{fg} be the success probability of a poaching attempt by f targeting a worker employed at g, and let p_{gf} denote the corresponding probability for a poaching attempt by g targeting a worker employed at f. The pair (p_{fg}, p_{gf}) depends in the firms' relative positions along a job ladder. In a frictionless labor market, workers sort toward firms that offer higher expected utility, through career advancement or wages and non-wage amenities, implying that upward moves are more likely than downward moves. According to this, I impose the following assumption:

- If f is ranked above g on the job ladder, then $p_{fg} > p_{gf}$.
- If g is ranked above f on the job ladder, then $p_{gf} > p_{fg}$.
- If f and g occupy similar positions on the job ladder, then $p_{fg} = p_{gf}$.

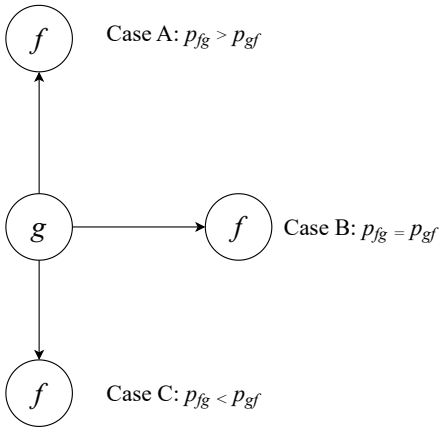


Figure 1: Job ladder and asymmetric poaching probabilities.

Strategic interactions and payoffs

I assume that in each period firms simultaneously choose between two actions: $x_i \in \{\text{NP (not poach)}, \text{P (poach)}\}$, for $i \in \{f, g\}$. Let π_i denote firm i's baseline per-period profit absent poaching. Poaching affects profits through worker reallocation. I assume that losing a worker reduces the target firm's profit by $\nu > 0$, the value of lost human capital. The poaching firm captures only a fraction $\alpha \in (0, 1)$ of that value, reflecting that human capital is partly firm-specific and thus imperfectly transferable. Accordingly, The one-shot payoff matrix is:

	NP	P
NP	(π_f, π_g)	$(\pi_f - \nu p_{gf},\ \pi_g + \alpha\nu p_{gf})$
P	$(\pi_f + \alpha\nu p_{fg},\ \pi_g - \nu p_{fg})$	$(\pi_f - \nu p_{gf} + \alpha\nu p_{fg},\ \pi_g - \nu p_{fg} + \alpha\nu p_{gf})$

This payoff structure yields a standard prisoner's dilemma. In particular, conditional on any action by the other firm, poaching provides a higher current payoff, while mutual non-poaching generates higher collective profit. The reason is that when both firms poach, each imposes a negative externality on the other through worker losses, so aggregate profits are lower than under mutual restraint. By contrast, mutual non-poaching internalizes this externality and is collectively efficient, but it is not privately incentive compatible in the one-shot interaction. This tension between privately optimal deviation and collectively efficient cooperation is a standard feature of models of tacit collusion and repeated games.

Furthermore, it is important to note that I abstract from the case in which the poaching firm captures more than the rival's loss (i.e., $\alpha > 1$). Such a case could arise if worker reallocation generates match-quality gains or other efficiency improvements that increase total surplus. Although empirically relevant in settings where mobility improves allocation, ruling it out sharpens attention on the "talent war" environment where poaching primarily reshuffling human capital across employers rather than creating net efficiency gains, making competition for workers increasingly costly for firms.

Infinitely repeated interaction

I now assume that the interaction between firms repeats indefinitely. Firms discount future payoffs with a common discount factor $\delta \in (0, 1)$. I focus on two canonical strategies that capture the key tension between short-run deviation incentives and long-run cooperation:

- **Grim trigger** (x^G): do not poach as long as the rival has never poached; following any deviation, poach forever.

- **Always defect** (x^{AD}): poach in every period.

Consider firm f on the cooperative path when firm g plays grim. If f cooperates, its continuation value is

$$V_f^C = \sum_{t=0}^{\infty} \delta^t \pi_f = \frac{\pi_f}{1-\delta}.$$

If instead f deviates by poaching once—thereby triggering permanent reversion to mutual poaching—its deviation payoff is

$$V_f^D = \big(\pi_f + \alpha\nu p_{fg}\big) + \delta \sum_{t=0}^{\infty} \delta^t \big(\pi_f - \nu p_{gf} + \alpha\nu p_{fg}\big).$$

Cooperation is sustainable if $V_f^C \geq V_f^D$,

$$\frac{\pi_f}{1-\delta} \;\geq\; \big(\pi_f + \alpha\nu p_{fg}\big) + \frac{\delta}{1-\delta}\big(\pi_f - \nu p_{gf} + \alpha\nu p_{fg}\big).$$

Rearranging yields the incentive compatibility condition for firm f:

$$\delta \;\geq\; \frac{\alpha p_{fg}}{p_{gf}}.$$

An analogous condition must hold for firm g:

$$\delta \;\geq\; \frac{\alpha p_{gf}}{p_{fg}}.$$

Therefore, mutual non-poaching can be sustained in equilibrium if and only if

$$\frac{\delta}{\alpha} \;\geq\; \max\left\{\frac{p_{fg}}{p_{gf}}, \frac{p_{gf}}{p_{fg}}\right\}. \tag{1}$$

Equation (1) highlights that asymmetric poaching success does not preclude cooperation, but it makes cooperation more difficult to sustain when one firm has a substantially higher probability of successfully poaching from the other (e.g., due to a higher position on the job ladder). In particular, if for some firm i the temptation to deviate is sufficiently strong such that $\alpha p_{ij} > p_{ji}$, then $\frac{\alpha p_{ij}}{p_{ji}} > 1$ and no $\delta \in (0,1)$ can satisfy the corresponding incentive constraint. In this case, grim-trigger cooperation breaks down and the unique equilibrium features persistent poaching. In the symmetric benchmark where $p_{fg} = p_{gf}$, condition (1) reduces to $\delta \geq \alpha$. Intuitively, cooperation is easier to sustain when firms are sufficiently patient (high δ) and when the private value extracted from a poached worker is limited (low α).

Overlapping ownership and firms' objective functions

So far, I abstract from overlapping ownership among employers and assume that firms maximize stand-alone profits. With overlapping ownership, however, firms may partially internalize the effects of their actions on rivals' profits, as common shareholders hold stakes in multiple firms. As a result, the relevant objective is no longer a firm's own profit in isolation, but rather a weighted sum of profits across firms linked through the ownership network. I posit that common ownership provides investors both the incentives to favor joint-profit maximization and the ability to influence managerial decisions in that direction (O'brien and Salop, 1999; Rotemberg, 1984; Posner et al., 2016; Backus et al., 2021; Newham et al., 2018). Formally, I model overlapping ownership by assuming that firm f evaluates outcomes according to the following objective function:

$$\begin{aligned} \pi'_f(x_f, x_g) = \; & (1-\chi)\,\pi_f(x_f, x_g) \; + \; \chi\big[\pi_f(x_f, x_g) + \pi_g(x_f, x_g)\big] \\ = \; & \pi_f(x_f, x_g) \; + \; \chi\,\pi_g(x_f, x_g). \end{aligned} \tag{2}$$

where $\chi \in [0, 1]$ captures the extent to which firm f internalizes firm g's profit due to common ownership between them, thereby shifting firm f's incentives toward joint-profit maximization. In the benchmark case of no overlapping ownership, $\chi = 0$ and firm f behaves as a pure profit maximizer. At the other extreme, when $\chi = 1$, firm f places equal weight on the rival's profit and effectively maximizes joint profits. In the intermediate region, $\chi \in (0, 1)$ delivers partial internalization, which weakens incentives for aggressive labor-market competition and poaching.

Using the original setting, the effective gain from poaching for firm f is reduced because it internalizes part of the rival's loss. In particular, when f poaches from g, firm f gains $\alpha\nu p_{fg}$ but also values the rival's loss νp_{fg} with weight χ. Thus, the net incentive-relevant gain is $(\alpha-\chi)\nu p_{fg}$. Similarly, firm g suffers a loss of νp_{fg} from losing a worker, but internalizes part of firm f's gain with weight χ. Considering that, the resulting stage-game payoff matrix in objective payoffs is:

	NP	P
NP	$(\pi'_f,\ \pi'_g)$	$\big(\pi'_f - (1-\alpha\chi)\nu p_{gf},\ \pi'_g + (\alpha-\chi)\nu p_{gf}\big)$
P	$\big(\pi'_f + (\alpha-)\nu p_{fg},\ \pi'_g - (1-\alpha\chi)\nu p_{fg}\big)$	$\begin{pmatrix} \pi'_f - (1-\alpha\chi)\nu p_{gf} + (\alpha-\chi)\nu p_{fg}, \\ \pi'_g - (1-\alpha\chi)\nu p_{fg} + (\alpha-\chi)\nu p_{gf} \end{pmatrix}$

Overlapping ownership and repeated-game collusion

Introducing overlapping ownership fundamentally alters firms' incentives. When shareholders hold stakes in multiple employers, firms no longer maximize stand-alone profits but instead partially internalize the effects of their actions on rival firms' payoffs. While cooperative outcomes in oligopolies are typically difficult to sustain due to short-run incentives to deviate, overlapping ownership weakens these incentives by reducing the effective gain from unilateral deviation. When firm f poaches a worker from firm g, it privately captures a fraction α of the value of the reallocated human capital, but it also internalizes part of the rival's loss with weight χ. As a result, the net deviation incentive is proportional to $(\alpha - \chi)$, rather than α as in the benchmark without common ownership. As χ increases, the temptation to poach diminishes, and when $\chi \geq \alpha$, poaching is no longer profitable even in the one-shot interaction. It is important to note this mechanism operates independently of enforcement or communication and arises solely from changes in firms' objective functions induced by ownership links.

In the infinitely repeated game, the reduction in deviation incentives induced by overlapping ownership relaxes the incentive-compatibility constraints required to sustain mutual non-poaching under grim-trigger strategies. With overlapping ownership, firm f's effective gain from unilateral deviation is reduced from $\alpha\nu p_{fg}$ to $(\alpha - \chi)\nu p_{fg}$. Proceeding analogously to the baseline case yields the following incentive constraint for sustaining mutual non-poaching under grim trigger:

$$\frac{\delta(1-\alpha\chi)}{\alpha-\chi} \;\geq\; \max\left\{\frac{p_{fg}}{p_{gf}}, \frac{p_{gf}}{p_{fg}}\right\}. \tag{3}$$

Since $\frac{1-\alpha\chi}{\alpha-\chi}$ is increasing in χ, overlapping ownership relaxes the incentive compatibility constraint and makes collusion more likely. Equation (3) highlights two central implications. First, holding fixed labor-market mobility fundamentals (p_{fg}, p_{gf}), greater ownership overlap (higher χ) lowers the minimum discount factor required to sustain mutual non-poaching, allowing collusion to arise even when firms are relatively impatient. In the limiting case as $\chi \to \alpha$, the deviation incentive vanishes and collusion can be sustained even in the one-shot interaction.

Second, holding firms' patience and human-capital transferability fixed (δ, α), higher common ownership facilitates collusion across the job ladder. In particular, ownership overlap mitigates the destabilizing effect of asymmetric poaching success by dampening the unilateral incentives of higher-ranked firms to exploit their advantage. These two points are illustrated

in Figure 2.

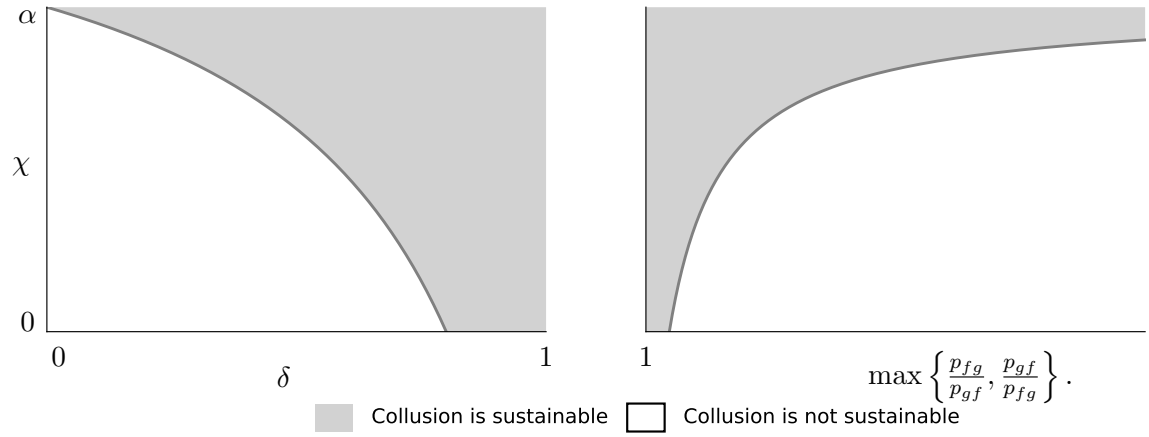


Figure 2: Overlapping ownership and collusion

Taken together, overlapping ownership expands the set of environments in which tacit labor-market collusion emerges in equilibrium. By weakening unilateral poaching incentives and reducing reliance on high discount factors, common ownership facilitates persistent non-poaching behavior and suppresses worker mobility, even in the absence of explicit agreements or communication between firms.

3 Data

In previous section, I show how overlapping ownership can reduce firms incentive to offer jobs to employees from other companies. That in turn can have important implication on employees' outside option and job transition. To test this hypothesis I combine two main source of data on public companies ownership structure and job transition between these firms.

First, I construct measures of overlapping ownership among all U.S. listed firms in the S&P 500 as of the last quarter of 2008, prior to the merger. For each firm pair (f, g) and quarter between 2006 and 2015, I represent firm f's ownership structure by a vector of cash-flow rights $\beta_f = (\beta_{f1}, \beta_{f2}, \ldots, \beta_{fS})$, where β_{fs} denotes the cash-flow share held by investor s in firm f. I measure overlapping ownership between firms f and g using the cosine similarity

between their ownership vectors, denoted by χ_{fg},

$$\chi_{fg} = \frac{\beta_f \cdot \beta_g}{|\beta_f|, |\beta_g|}. \tag{4}$$

which provides a symmetric and scale-free measure of common ownership that captures the extent to which the same investors hold similar portfolio shares across firms. To construct these measures, I use information on the cash-flow rights of institutional investors from quarterly 13F filings, as collected and digitized by Backus et al. (2021) from the Securities and Exchange Commission (SEC) website. I further complement this dataset with information on prices and shares outstanding obtained from the Center for Research in Security Prices (CRSP).

My second dataset on job transitions is based on a large collection of resume data from lightcast database. The data is derived from cv postings on online job search platforms and other professional platforms. Matching the employers information between two dataset, I obtain the educational and career history of almost 5 million skilled workers that obtain a bachelor degree from a US college between 1995 and 2020 and has worked once in a S&P500 company listed in my sample. The number account for 24% all college graduates in my dataset. Comparing those number with the total bachelor graduates in united states during the same period it shows data on average account for approximately 55% of total US college graduates that are estimated to be around 38 million graduates [2].

Using this data, I construct a panel of annual job transitions and ownership similarities between S&P 500 companies. The former represents the total number of job transitions in each year, while the latter is the average ownership similarity for the given year.. Note that for any pair of firms (i,j) there are two observations each year. One shows the job transitions from firm i to firm j and the other indicates the job transitions from firm j to firm i. That allow me to distinguish between inflows and outflows for firms within each company pairs.

4 Empirical strategy

Empirically testing whether overlapping ownership affects firm behavior is challenging, as it is often closely related to firm-specific and aggregate economic conditions, such as changes in industry concentration (Doidge et al., 2017; Lewellen and Lowry, 2021). To address this issue, I exploit the plausibly exogenous variation in ownership structure caused by the merger

[2] See National Center for Education Statistics: https://nces.ed.gov/programs/digest/d23/tables/dt23_318.10.asp

between two large institutional investors, BlackRock and Barclays Global Investors (BGI). This approach is inspired by He and Huang (2017) and has been utilized by Azar et al. (2018) to examine the anti-competitive effects of common ownership on airline ticket prices.

BlackRock-BGI Merger

The merger was first announced on June 11, 2009, when BlackRock submitted a $13.5 billion bid to acquire Barclays Global Investors (BGI). The bid was successful and the deal was formally completed on 1 December 2009. As a result, BlackRock more than doubled its assets under management, growing from $1.44 trillion to approximately $3.29 trillion, and became the world's largest investment management company.

The merger had a substantial impact on the ownership structure of the companies. Prior to the merger, in the first quarter of 2009, BlackRock and BGI were the top investors in approximately 17.8% of S&P 500 companies. After the merger, in the first quarter of 2010, the combined assets positioned BlackRock as the top investor in 34.8% of S&P 500 firms and increased the average ownership similarity across the firms by 4.4%. Importantly, Barclays' earlier attempt to sell part of the division to investors other than BlackRock indicates that the move was not originally driven by considerations about the potential effects of combining the two companies' portfolios(Azar et al., 2018).

Identification

To study the relation between job mobility and ownership similarity I apply the following benchmark model at the company pair-year level:

$$y_{fgt} = \beta\, \chi_{fgt} + \lambda_{fg} + s^{j}_{ft} + s^{d}_{gt} + \epsilon_{fgt} \tag{5}$$

Where χ refers to the average cosine similarity between the ownership structure of two firms during year t, λ_{fg} indicates the firm-pair fixed effects; s^{j}_{ft} and s^{d}_{gt} denote the 2-digit sector-year fixed effects for firms f and g; andy_{fgt} indicates the measure of job transitions between two firms.

In equation (5), y_{fgt} includes the intensive and extensive margins of job transitions between firms f and g during year t. The intensive margin of job flows is represented by the logarithm of the number of job transitions, while the extensive margin is defined by a dummy variable that takes the value of zero if no job transition occurs between the two companies during

year t and one otherwise. Furthermore, I examine the joint effect of these two margins using the following quasi-maximum likelihood (QML) Poisson setup.

$$y_{fgt} = exp\left(\beta' \chi_{fgt} + \lambda_{fg} + s^j_{ft} + s^d_{gt})\epsilon'_{fgt}\right. \tag{6}$$

where y_{fgt} represents the number of job transitions. This specification is well-suited to capture the count nature of job flows and accounts for variations arising from both intensive and extensive margins.

To obtain an unbiased estimate of β and β' in equations (5) and (6), it is essential to ensure that ownership similarity is not correlated with the error terms ϵ_{fgt} and ϵ'_{fgt}. Several potential confounding factors could violate this condition, as job mobility and ownership similarity are both strongly correlated with firm characteristics and broader macroeconomic conditions.

To overcome this identification problem, we exploit the exogenous variation in overlapping ownership among firms that is caused by BlackRock-BGI merger. To this end we use the following first stage IV estimation:

$$\chi_{fgt} = \beta'' \; MergerImpact_{fg} \times Post\text{-}merger_t + \lambda_{fg} + s^j_{ft} + s^d_{gt} + \varepsilon_{fgt} \tag{7}$$

Where *Post-merger* is a dummy variable equal to one for years after 2008 ($t > 2008$), and $MergerImpact$ is a firm-pair level measure according to hypothetical effect of merger before the BlackRock-BGI deal announced. To construct this measure, I begin by calculating the ownership similarity for all firm-pairs in the last quarter of 2008, prior to the merger. To achieve this, I use the overlapping ownership index, $\chi^{2008Q4}_{fg} = \cos(\beta^{2008Q4}_f, \beta^{2008Q4}_g)$, , which I derive in equation (8) in section (3). That measures the cosine of the angle between the ownership share vectors of all shareholders in firms f and g. calculate ownership similarities under a hypothetical scenario where the BlackRock-BGI merger occurs in the end of 2008. To do this, I consolidate the assets of the two companies and recalculate their joint ownership share across all S&P 500 companies. I define this counterfactual ownership similarity as $\bar{\chi}^{2008Q4}_{fg} = \cos(\bar{\beta}_f{}^{2008Q4}, \bar{\beta}_g{}^{2008Q4})$. Finally, I construct a variable to capture the implied change in ownership similarity caused by the merger for each firm pair (f, g) as follows:

$$\Delta\chi_{fg} = \bar{\chi}^{2008Q4}_{fg} - \chi^{2008Q4}_{fg} \tag{8}$$

The Figure (3) shows the distribution of $\Delta\chi_{fg}$. The distribution is right-skewed, indicating that company pairs in the right tail experience a significantly larger increase in ownership

similarity compared to the average pair. While those in the top tertile would see a 4.6 percentage point rise, the rest of the company pairs experience only a 1.1 percentage point increase on average. This motivates me to define the $MergerImpact_{fg}$ in equation (7) as a dummy variable equal to 1 if the company pairs fall within the top tertile of $\Delta\chi_{fg}$ and 0 otherwise. As a robustness check, I also use $\Delta\chi_{fg}$ directly to instrument ownership similarity in equation (7).

Lastly, since the merger impact varies at the firm-pair level, we cluster standard errors at the firm-pair level in all estimations to account for potential serial correlation and heteroskedasticity (Bertrand et al., 2004).

5 Results

This section presents the results of our main regressions examining the impact of the BlackRock-BGI merger on firms' ownership similarity and job mobility. I discuss the main difference-in-differences results and the associated event studies. Additionally, I also describe the IV-DID setup that I use to quantify the causal effect of employers' overlapping ownership on employees' job mobility.

5.1 Reduced form results: The impacts of BlackRock-BGI merger

We start by presenting the results of the reduced-form estimations, directly examining the relationship between job transitions and our instrument, which captures exogenous variations in ownership similarity caused by the merger. Table (2) presents the results. Column 1 indicates that firm pairs in the top tertile of predicted increases in ownership similarity experienced, on average, a 2.8% greater rise in ownership similarity compared to the rest of the S&P 500 companies in my sample.

Column 2 examines the impact on the volume of job mobility using a linear regression, where the dependent variable is the logarithm of job transitions for each company pair in each year. The results indicate that, conditional on having job transitions, the number of employees moving from one firm to another decreased by 8.6% for firm-pairs with high increases in overlapping ownership after the merger. This result suggests that talent turnover between the two firms substantially decreased, consistent with the model's prediction that higher ownership similarity reduces firms' incentives to acquire employees from each other.

While Column 2 reports results on the intensive margin of job transitions between firms, Table (1) shows that approximately 25% of company pairs do not exchange any employees in a given year during my sample period between 2006 and 2015. Column 3 focuses on the extensive margin of job mobility by running a linear regression where the dependent variable is a dummy that takes the value of one if there is any job transition between two firms, and zero otherwise. The estimate in Column 2 suggests that firm-pairs in the top tertiles of predicted increases in ownership similarity are 1.2% less likely to poach any employees from each other after the merger. However, this effect is not statistically significant.

Column 3 presents the results for the reduced-form estimation of equation (6), examining the impact on job mobility counts, which capture both the intensive and extensive margins of job transitions between firms. Considering both margins, I find that firm pairs in the top tertile of predicted increases in ownership similarity experienced an 11% ($e^{-0.116} - 1$) lower employee flows between them after the merger compared to other company pairs.

Figure (4) shows the dynamics of the BlackRock-BGI merger's impact on ownership similarity. The event study is conducted at the quarterly level, allowing us to closely track changes in ownership similarity among S&P 500 companies before and after the deal's announcement in June 2009 and its completion in December 2009. The figure shows that overlapping ownership among firm pairs in the top tertile of predicted increases in ownership similarity rose sharply and significantly compared to other firms following the merger's completion in December 2009.

Next, I examine the dynamics of the relationship between changes in the ownership similarity induced by the merger and job transitions among affected firms.To do so, I estimate the year-by-year gap in job mobility between firm pairs in the top tertile of predicted increases in ownership similarity and other firm pairs. Figure 5 presents these estimated effects, highlighting two key insights. First, the impact of the merger does not predate the merger, confirming the validity of our strategy to use the merger as a source of exogenous variation in ownership similarity. Second while the impact on extensive margin of job transition is short term and transitory the impact on extensive margin persist over time. Second, while the effect on the extensive margin of job transitions is short-term and transitory, the impact on the intensive margin persists over time. Similarly, the dynamics of job transition counts, which account for both margins, reveal that the immediate post-merger effect is primarily driven by the intensive margin, whereas over time, the extensive margin becomes the dominant driver as the intensive margin effect fades.

For my main analysis, I restrict the sample to firm-pairs with at least three job transitions between the two firms prior to the merger. This restriction is motivated by the desire to exclude firms that do not compete for a common pool of talent. Table (3) demonstrates that the results get stronger when we use alternative samples that include firms with a higher number of prior job transitions.

5.2 IV estimation: Quantifying the impact of ownership similarity on job transition

In this section, I use the predicted exposure to the merger's impact as an instrument for changes in ownership similarity between firm pairs before and after the merger. This approach allows me to quantitatively estimate the causal effect of employers' ownership similarity on employees' job mobility. Columns (1) to (3) in Table 4 present the results of our baseline instrumental variable regression, that I explained in section 4, where I use a binary variable to capture the cross-sectional variation in exposure to the merger's impact.

Panel A of Table 4 reports the second-stage estimation results. The findings indicate that a 1% increase in ownership similarity reduces job mobility by -4.31% ($e^{-.04403} - 1$). Of this decline, 2.95% is driven by the intensive margin, which persists over time, while the 0.54% comes from the extensive margin, which is statistically insignificant and fades over time.

Panel B reports the first-stage estimation, showing that our instrument, *Merger Impact* $\times$ *Post-merger* ($year > 2008$), has a positive and statistically significant effect on ownership similarity. This confirms that the merger triggered changes in the ownership similarity in the post-merger period and thus satisfies the relevance condition. A key concern with the relevance condition is the potential weak instrument problem. To address this, I report the Kleibergen-Paap F-test, which ranges between 37.50 and 42.15 in our baseline regressions, mitigating concerns about instrument weakness.

Columns 4-6 present the results using an alternative approach to capture the impact of the merger, where I replace the binary measure with the continuous measure of predicted increases in ownership similarity, $\Delta\chi$, that is derived in Equation (8). The second-stage results in Panel A of Table 4 show qualitatively similar patterns, with a smaller estimated impact on the count of job transitions and the intensive margin, but a stronger effect on the extensive margin. Moreover, the first-stage results in Panel B indicate that $\Delta\chi$ exhibits approximately a one-to-one correlation with ownership similarity, suggesting that the predicted changes were accurately realized after the merger. The Kleibergen-Paap F-test for

the continuous measure ranges between 108.19 and 120.18, confirming the strength of the instrument.

5.3 Job transitions and career stages

In the previous section, we established that greater ownership similarity between employers reduces employees' job mobility between those firms. In this section, we take a closer look at how higher ownership similarity affects the composition of job transitions and which individuals are most affected. We begin by examining the differential impact on job transitions across various career stages. To do so, we exploit variation across different cohorts and time periods.

Figure 6 illustrates how job transitions are distributed across cohorts and over time for a sample of individuals who, at some point between 2006 and 2015, moved between S&P 500 companies. The sample includes not only transitions between S&P 500 firms but also other job movements these individuals experienced during the same period. It comprises approximately 1.7 million job transitions from 25 different cohorts of individuals who obtained their bachelor's degrees between 1995 and 2020. Panel (a) of Figure 6 shows the share of total job transitions attributable to each cohort. Panels (b) and (c) demonstrate that, for each cohort, the highest rate of job transitions occurs in the year of bachelor's graduation, followed by a steady decline over time. Interestingly, a substantial share of job transitions takes place even before individuals complete their undergraduate degrees.

Figure 7 restrict the sample to job transitions between S&P 500 companies, which represent approximately 16% of all observed job transitions. The figure categorizes these transitions into three main career stages. Approximately 32% of transitions occur during or before the year of graduation. Most of these job mobilities relates to graduation year that marks the transition from university to the labor market, as well as the four years preceding graduation that mostly reflects the job experiences during the undergraduate studies.The second stage is the early career that defines the first ten years following the graduation and accounts for more than 50% of all transitions, with 32% taking place within the first five years. The late career stage, encompassing transitions occurring more than ten years after graduation, represents just 15% of total job transitions.

To study the effect of employers' ownership similarity on composition of job transitions. I estimate the following reduced form equation:

$$y^{C}_{fgti} = \beta \; MergerImpact_{fg} \times Post\text{-}merger_{t} + \lambda_{fg} + s^{j}_{ft} + s^{d}_{gt} + \epsilon_{fgti} \tag{9}$$

Where χ refers to the average ownership similarity between two firms f and g during year t, λ_{fg} indicates the firm-pair fixed effects; s^{j}_{ft} and s^{d}_{gt} denote the 2-digit sector-year fixed effects for firms f and g.

Although the specification closely follows our benchmark model in Equation 5, the unit of observation here is at the job transition level and includes all transitions between S&P 500 companies used in our baseline regression. We estimate a separate regression for each of the three defined career stages, where y^{C}_{fgti} is a binary variable equal to 1 if the job transition occurs during the career stage C, and 0 otherwise. In the first specification, $y^{Bac}_{fgti} = 1$ if the transition occurs in the bachelor's graduation year or earlier. In the second specification, y^{EC}_{fgti} takes the value of one if the transition occurs during the early career stage, defined as the first ten years following graduation. In the third specification, y^{LC}_{fgti} is equal to one if the transition takes place more than ten years after graduation, representing the late career stage. These three specifications allow us to examine how the distribution of job transitions across different career stages varies with changes in ownership similarity.

The results are presented in Table (5). They indicate that job mobility during the early career stage decreased by 2.3%, which is offset by a 1.6% increase in late career mobility and a 0.7% increase in transitions occurring during or before the graduation year. However, the latter effect is not statistically significant. Figure (7) illustrates the dynamic effects over the period from 2006 to 2015, showing how increased ownership similarity—induced by mergers—impacts the rate of job transitions across different career stages.

5.3.1 Job transition to large and productive firms in early career stage

A large body of research highlights the role of firms in shaping labour market outcomes, showing that workers with similar characteristics can earn different wages depending on their employer (Card et al., 2013; Goldschmidt and Schmieder, 2017; Card et al., 2018; Sorkin, 2018; Abowd et al., 2018; Bonhomme et al., 2019). One strand of this literature emphasizes the importance of employer size (Moore, 1911; Brown and Medoff, 1989; Oi and Idson, 1999; Bloom et al., 2018; Colonnelli et al., 2018; Arellano-Bover, 2024), while another highlights the role of employer productivity (Bagger et al., 2014; Bartolucci et al., 2018;

Haltiwanger et al., 2018; Lochner and Schulz, 2024). Taken together, these studies find that larger and more productive firms are positively associated with higher earnings and stronger career development, with these effects being especially important during the early stages of workers' careers (Arellano-Bover, 2024; Deming, 2023).

In this subsection I study how ownership similarity affect the early career transitions toward large and productive firms where I use the number of employees and total factor productivity (TFP) to compare firms. To estimate total factor productivity, I use a sample of S&P500 companies between 1999 and 2008 before the merger take place to estimate the following industry-specific Cobb-Douglas production function, assuming that all firms within a sector share the same technology:

$$y_{it} = \beta_s^{\nu} \nu_{it} + \beta_s^{k} k_{it} + \chi_{it}$$

where, y_{it} is the output and measured by the logarithm of sales. ν_{it} represents the flexible input and it is measured by logarithm cost of goods sold (COGS). It bundles all expenses directly attributable to the production of the goods sold by the firm and includes materials, energy and labor cost. k_{it} denotes the logarithm of physical capital, measured by the gross value of property, plant and equipment and is considered a fixed input in our framework. ω_{it} indicates the productivity and nominal values adjusted by 1999 prices.

To estimate the output elasticities, we face a standard simultaneity bias, which arise because of potential correlation between productivity and input choices. To overcome this problem, we follow the control function approach literature (Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg et al. (2015)). As in Díez et al. (2021) and De Loecker et al. (2020), we assume that productivity follows a first-order Markov process and can be expressed by inverting the demand for cost of goods. That allow us to form the following system of equation and solve for industry specific output elasticities.

$$\begin{aligned} y_{it} &= \beta_s^{\nu} \nu_{it} + \beta_s^{k} k_{it} + \omega_{it} \\ \omega_{it} &= \rho_s \omega_{it-1} + \zeta_{it} \\ \omega_{it} &= h^{-1}(\nu_{it}, k_{it}) \end{aligned}$$

Where $h^{-1}(.)$ indicates the inverse demand, approximated by a third-order polynomial function. To solve and estimate the parameters, we follow the two-step IV-GMM approach from Ackerberg et al. (2015).

Using theses measures, figure (9) illustrates patterns of job mobility based on the relative size and productivity of origin and destination employers. Panels (a) and (b) show that upward moves are concentrated in the top tertile of the distribution where workers transition to substantially larger and more productive firms. Panels (c) and (d) focus on early-career transitions and show that job moves within the first ten years after graduation are more likely to occur in the tails of the productivity ratio distribution, meaning that workers are more likely to be relocated to firms with markedly different productivity levels. This dispersion suggests that early-career mobility plays a role in upward and downward job mobility when we compare employers by productivity. By contrast, sorting based on employer size exhibits a more muted pattern, with early-career transitions less concentrated in the tails of the firm-size distribution.

Table 6 reports the differential effect of higher ownership similarity across company pairs in the different tertiles of size and productivity ratios. That allows us to examine how common ownership between employers affects the likelihood of moving to significantly larger, and more productive employers during the early stages of a career. Column (1) presents the baseline estimate including all job transitions, showing that the share of early-career mobility decreases by 2.3% among company pairs in the top tertile of predicted increases in ownership similarity compared to other firm pairs following the merger. Columns (2)-(4) split the sample based on the relative size of destination to original firms, with size measured by each firm's number of employees in the year the transition occurred. The results show that the negative effect is concentrated among the transitions that fall in the top tertile of size ratio while the effect is small and statistically insignificant for transitions outside this group. That suggest ownership similarity reduces the likelihood of moving into significantly larger firms. A similar pattern emerges when I examine the relative productivity of destination and origin firms. Columns (5)–(7) show that job transitions to significantly more productive firms declined by 10.3%, while the effects on transitions between other firm pairs are small and statistically insignificant. It is important to note that the sample of firms for which we can estimate TFP is smaller than in the main analysis, and overall the effect appears stronger in this subsample.

Taken together, these results provide evidence that higher ownership similarity not only reduce the job transition in early career stage but also it disproportionately hampers early-career workers' opportunities to sort into large and productive firms. Since such transitions are particularly important for long-term wage growth and career development, higher common ownership among employers can distort labor market outcomes by limiting upward

mobility.

5.3.2 Early career job transitions across different employees

In the previous subsection, I examined how common ownership among employers differentially affects early-career job transitions across company pairs. In this subsection, I turn to how these differential effects vary with employee characteristics, focusing specifically on gender and field of study.

I began by examining the role of gender, focusing in particular on how the impact of ownership similarity on job mobility varies across career stages for male and female individuals. Gender can be inferred from individuals' names for approximately 58% of all job transitions. Within this subsample, 40% of transitions involve female individuals, while 60% involve male individuals.

As shown in Figure (11), 35% of job transitions among female individuals occur during or before the graduation year, compared to 30% for male individuals. The early career transitions, defined as those within the first ten years after graduation, account for 53% of transitions among women and 54% among men. The late career stage transitions represent 13% of the total for female individuals and 17% for male individuals. These figures suggest that female individuals are more likely than their male counterparts to transition jobs during or before graduation. However, they are less likely to change jobs in the later stages of their careers.

To examine the differential impact over career stages by gender, I estimate Equation (9) separately for subsamples of female and male individuals. The results are presented in columns (2)–(7) of Table (7). Our estimates suggest that the previously observed pattern, characterized by a decline in early career job transitions and an increase in late career transitions, is primarily driven by male individuals. I further explore whether this shift affects the overall gender composition of job transitions. The estimate in column (1) of Table (7) reveals a slight decline in the likelihood of a job transition being undertaken by a female individual relative to a male, although this effect is not statistically significant.

One factor that may help explain these results is the difference between male and female individuals in terms of their field of study and educational background. A large body of literature has documented the underrepresentation of women in STEM fields (Beede et al., 2011; Kahn and Ginther, 2017; Cimpian et al., 2020; Owen, 2020; Jiang, 2021; Saltiel, 2023;

Denison, 2023). To define STEM fields, I follow Peri et al. (2015) and use the classification adopted by the U.S. Department of Homeland Security for determining eligibility for the F-1 Optional Practical Training (OPT) extension. In our sample, roughly 22% of job transitions are carried out by individuals with a STEM bachelor's degree. Among these, 74% are made by male individuals, whereas male individuals account pnly for 55% of job transitions in non-STEM fields. This pattern highlights the strong male dominance in STEM fields inline with previous literature.

To explore this further, I first examine how the effect on job transitions varies across career stages for individuals with and without a bachelor's degree in a STEM field. Specifically, I estimate equation 9 separately for the subsamples of individuals with and without a STEM bachelor's degree. Table 5 presents the results, showing that for individuals with a STEM bachelor's degree, , greater ownership similarity leads to a 6.9% decline in the share of job transitions during the early career stage, which is offset by a higher share of transitions later in the career. In contrast, the composition of job transitions among individuals without a STEM bachelor's degree remains largely unaffected. While STEM fields are typically male-dominated, and men and women tend to differ in their mobility patterns across career stages, Table (9) suggests that gender does not account for the observed decline in early-career job transitions associated with higher ownership similarity.

Finally, I examine how the effect of higher ownership similarity on job mobility varies by career stage and the quality of the graduating institution. Table 10 presents these results. Columns (2)–(4) focus on individuals who graduated from the top 100 universities while Columns (5)–(7) reports the estimates for subsample of individuals who graduated from other institutions.The results indicate that ownership similarity has roughly twice the negative effect on early-career job mobility among graduates from top universities compared to those from other institutions. However, the difference between the two groups is not statistically significant.

Figure (12) summarizes the results of this subsection and illustrates how the effect of employers' common ownership on early-career job transitions varies across employee characteristics. In particular, the figure shows that the negative impact of ownership similarity is most pronounced among graduates from STEM fields, who experience a 6.9 percentage point decline in early-career job transitions, substantially larger than the 2.3 percent decrease observed for the average employee in the dataset.

6 Conclusion

Conclusion This paper provides new empirical evidence on how overlapping ownership among employers affects job mobility. Leveraging a quasi-experimental setting based on the 2009 merger between BlackRock and Barclays Global Investors (BGI), I show that increases in ownership similarity between firms significantly reduce the flow of employees between them. The results indicate that when firms share common institutional owners, their incentives to compete for workers weaken, leading to fewer job transitions and a narrowing of employees' outside options. These findings reveal an important, yet often overlooked, channel through which financial interconnections among firms can shape labour market outcomes.

The paper also highlights substantial heterogeneity in these effects across workers and employers. Reductions in mobility are especially pronounced during the early stages of workers' careers and among transitions toward larger and more productive firms—those typically associated with higher wages, faster learning, and stronger long-term career prospects. This pattern suggests that common ownership constrains upward mobility by limiting access to high-quality employers. Moreover, the negative effects are more severe for graduates in STEM fields and individuals from top-ranked universities, implying that the most mobile and high-potential workers face the greatest restrictions when ownership ties among employers are stronger.

Taken together, these results suggest that rising common ownership in U.S. capital markets may have broader labour market consequences beyond its well-documented effects on product market competition, corporate governance, and innovation. By dampening inter-firm mobility, overlapping ownership can reduce the efficiency of labour market matching, suppress wage growth, and reinforce inequality in career trajectories. From a policy perspective, these findings underscore the need for antitrust and regulatory authorities to consider the labour market implications of ownership concentration and inter-firm coordination.

Figure 3

The implied effect of BlackRock-BGI merger on ownership similarity of S&P 500 companies

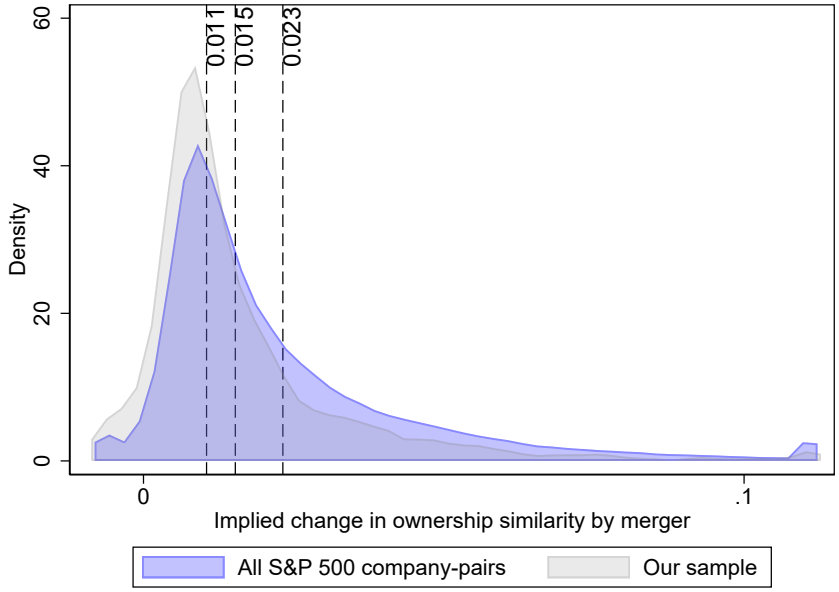
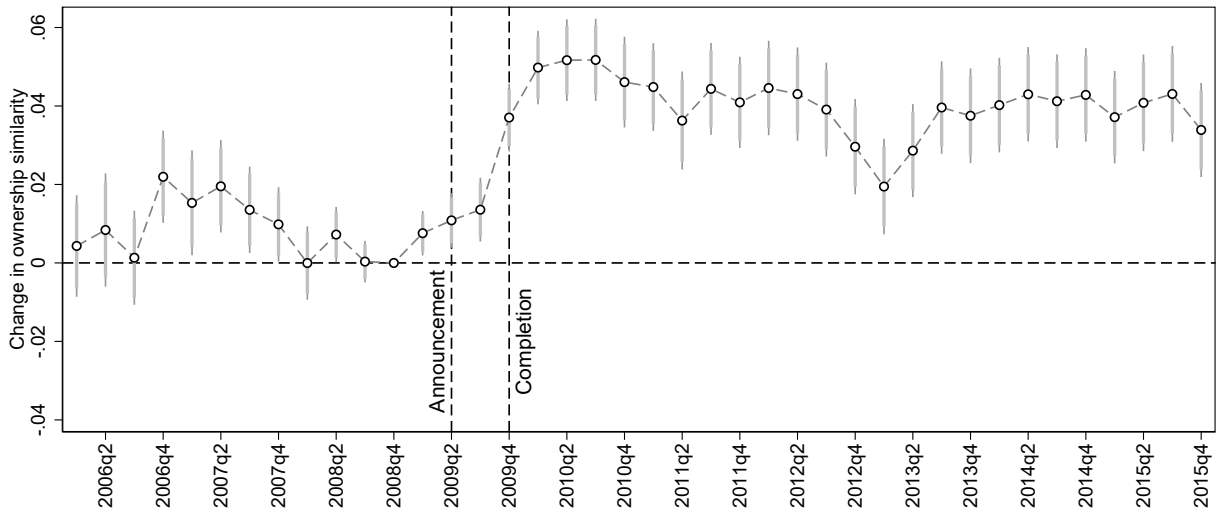


Figure shows the distribution of the implied change in ownership similarity ($\Delta\chi_{fg}$), , that is calculated in equation (8), based on the hypothetical BlackRock-BGI merger at the end of 2008. The distributions are color-coded to distinguish different samples. Blue represents all the S&P 500 company-pairs, while gray denotes the distribution for the S&P 500 company-pairs included in our analysis. The dashed lines represent the change in ownership similarity for the bottom tertile, median, and top tertile of all S&P 500 company pairs. Note that the average

Figure 4

The effect of BlackRock-BGI merger on ownership similarity of S&P 500 companies



The figure shows the quarter-by-quarter effect of BlackRock-BGI merger on ownership similarity of S&P 500 companies before and after the announcement and completion of the deal in June and December 2009. The impact is captured by the coefficients $\beta_{t'}$ in following regression

$$\chi_{fgt} = \beta\ MergerImpact_{fg} \times \sum_{t'=2006Q1}^{2015Q4} \beta_{t'} \times \mathbb{1}(t = t') + \lambda_{fg} + s^{j}_{ft} + s^{d}_{gt} + \varepsilon'_{fgt}$$

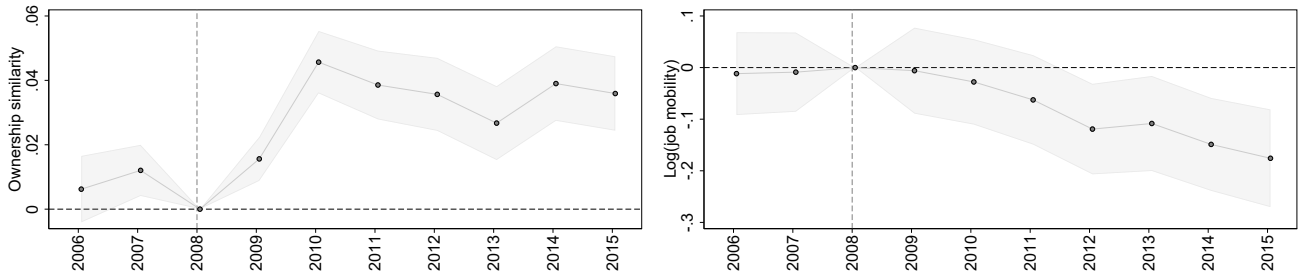
Where $MergerImpact_{fg}$ is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of the implied increase in ownership similarity after the BlackRock-BGI merger. The implied increase in ownership similarity ($\Delta\chi_{fg}$) calculated in equation (8) using the hypothetical BlackRock-BGI merger at the end of 2008; λ_{fg} indicates the firm-pair fixed effects; s^{j}_{ft} and s^{d}_{gt} denotes the 2-digit sector-year fixed effects for the firms f and g. χ refers to the cosin similarity between the ownership structure of two firms in quarter t. Note that the gray lines plot the 95% confidence interval.

Figure 5

The effect of higher ownership similarity on job trnasitions

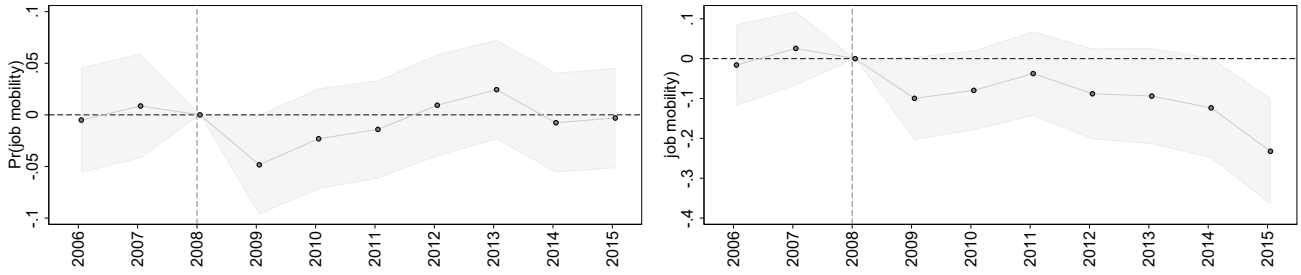
(a) Ownership similarity

(b) Log(job transition)



(c) Pr(job transition)

(d) Number of job transitions



The figure shows the year-by-year effect of higher ownership similarity induce by the merger between 2006 and 2015. The impact is captured by the coefficients $\beta_{t'}$ in following regression

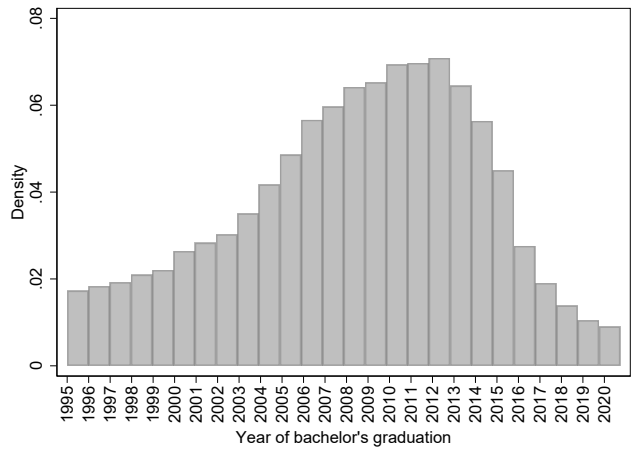
$$y_{fgt} = \beta\ MergerImpact_{fg} \times \sum_{t'=2006}^{2015} \beta_{t'} \times \mathbb{1}(t = t') + \lambda_{fg} + s^{j}_{ft} + s^{d}_{gt} + \varepsilon'_{fgt}$$

Where y_{fgt} is the average ownership similarity among firm-pairs f and g during year t in panel(a) , the logarithm of job transitions from origin firm f to destination firm g during year t in panel(b), a dummy variable that takes the value of 1 if there is a job transition from firm f to firm g during year t in panel(c), and number of job transitions from origin firm f to destination firm g during year t. $MergerImpact_{fg}$ is a dummy variable that takes the value of 1 if the firm pairs are in the top quartile of the implied increase in ownership similarity after the BlackRock-BGI merger. The implied increase in ownership similarity ($\Delta\chi_{fg}$) calculated in equation (8) using the hypothetical BlackRock-BGI merger at the end of 2008; λ_{fg} indicates the firm-pair fixed effects; s^{j}_{ft} and s^{d}_{gt} denotes the 2-digit sector-year fixed effects for the firms f and g. Note that the gray shade plot the 95% confidence interval.

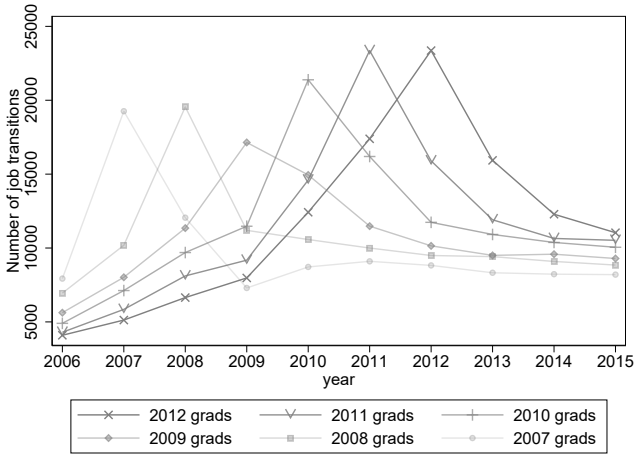
Figure 6

Job transitions across time and cohorts

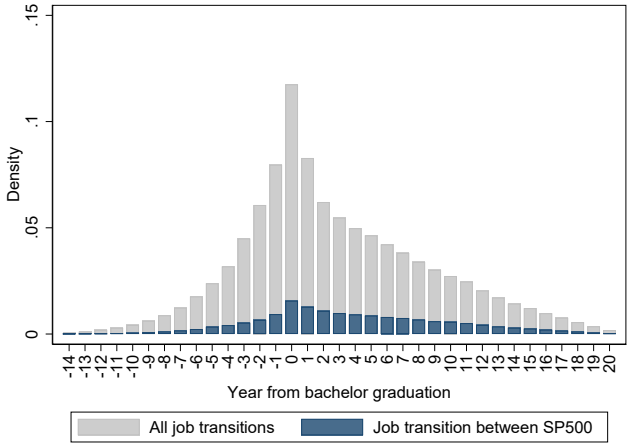
(a) Total job transitions by each cohort



(b) Timing of job transitions for each cohort



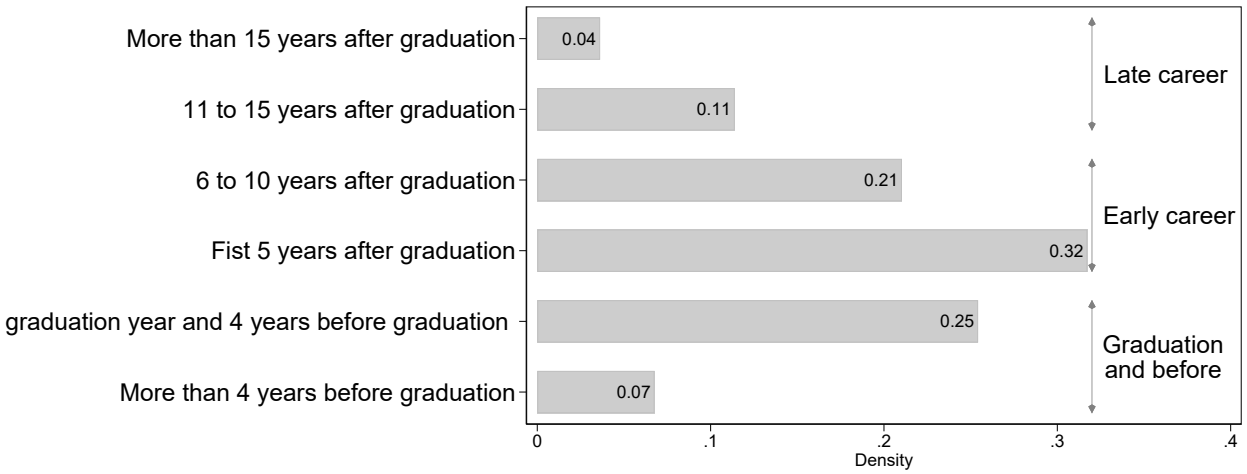
(c) Job transitions by year from graduation



The figure presents information on all job transitions carried out by a sample of individuals who moved between S&P 500 companies between 2006 and 2015. Panel (a) shows the total number of job transitions by cohort. Panel (b) displays the timing of job transitions separately for a sample of six cohorts who completed their bachelor's degrees between 2007 and 2012. Panel (c) illustrates the density of job transitions by years from bachelor's graduation. The gray shading represents all job transitions, while the blue shading highlights only transitions between S&P 500 companies.

Figure 7

Job transitions by career stages

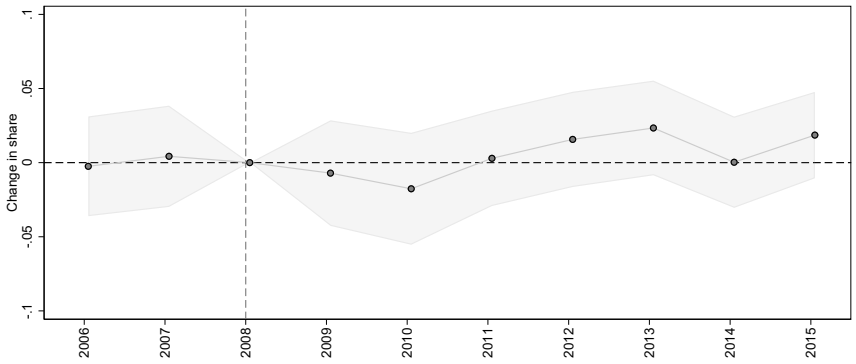


The figure illustrates how job transitions between S&P 500 companies from 2006 to 2015 are distributed across different career stages.

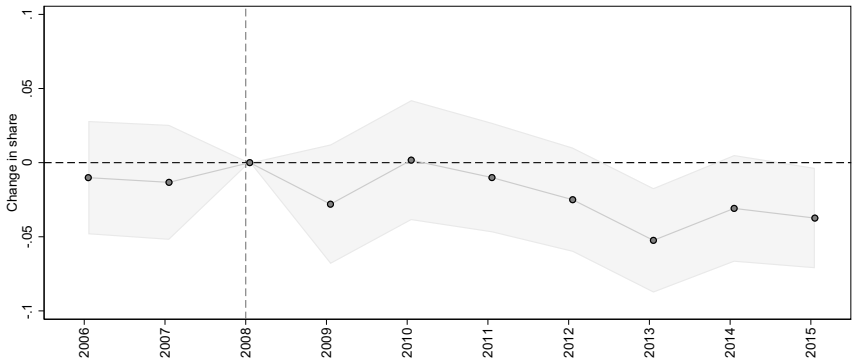
Figure 8

Higher ownership similarity and job transitions across different career stages

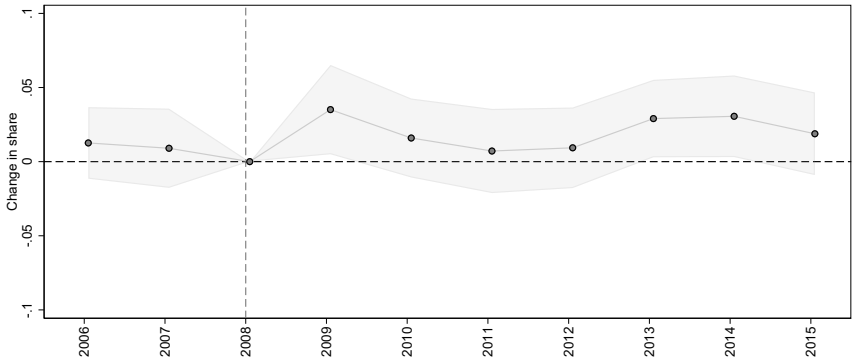
(a) Graduation year and before



(b) Early career



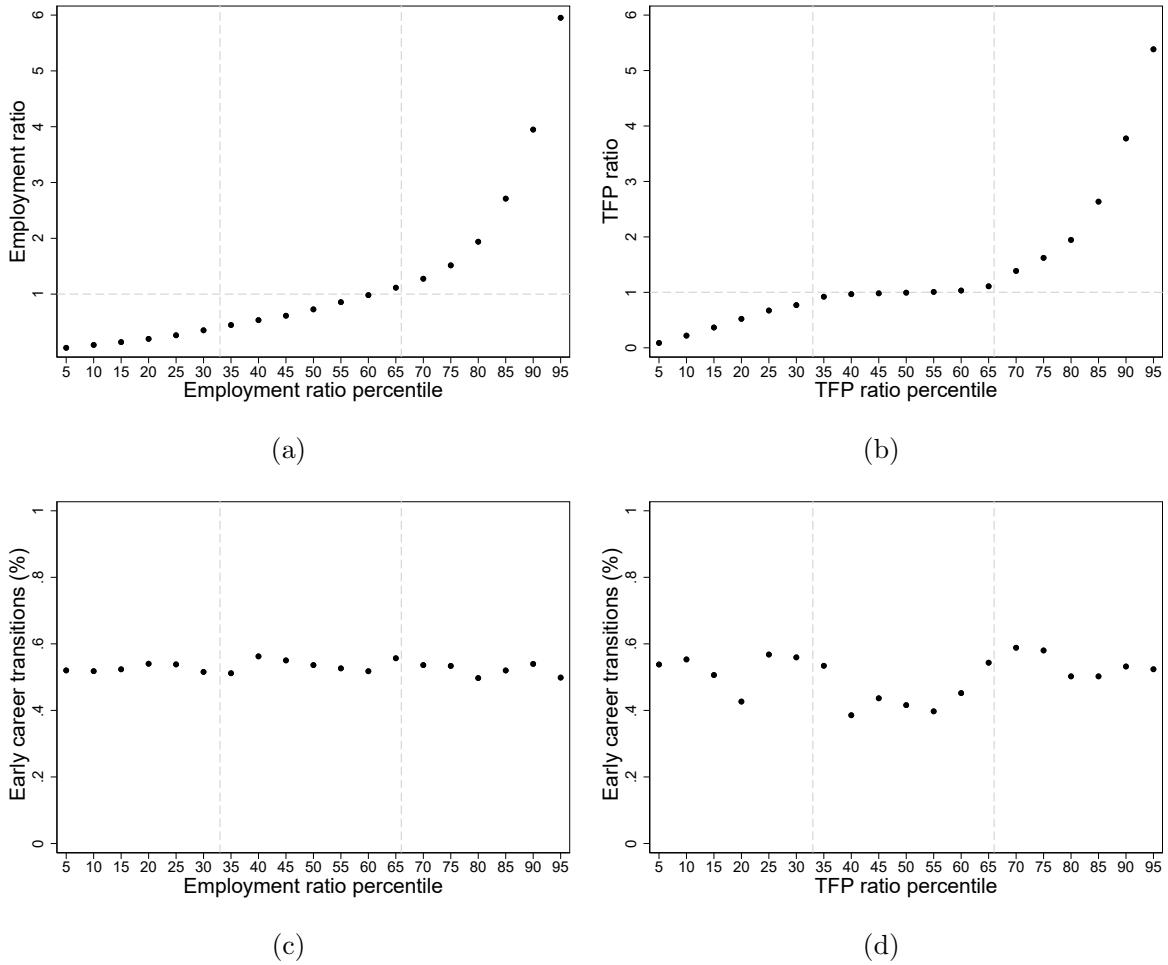
(c) Late career



The figure illustrates how higher ownership similarity influences the composition of job transitions across different career stages. Panel (a) shows the change in the share of job transitions that occur during or before the bachelor's graduation year. Panel(b), indicates the change in share of job transitions that occurs in first 10 years after the bachelor graduation. panel(c) shows the change in share of late career job transition. Note that The figure corresponds to the event study estimates reported in columns (1)–(3) of Table (5), with gray shaded areas representing 95% confidence intervals.

Figure 9

Job transitions based on employers' relative size and productivity



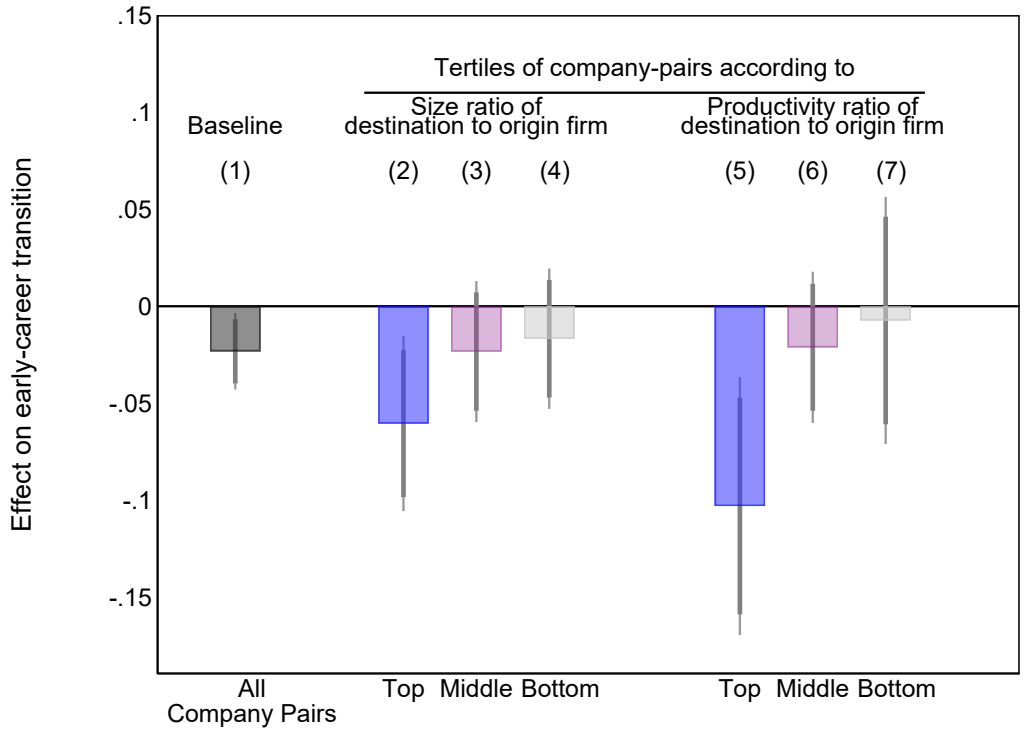
(a) (b)

(c) (d)

The figure illustrates patterns of job mobility based on the relative size and productivity of origin and destination employers. In all panels, employer size is measured by the number of employees, and productivity is measured by total factor productivity (TFP) in the year the job transition occurred. Panels (a) and (b) show that roughly one third of transitions involve moves to significantly larger and more productive firms. Panels (c) and (d) display the share of transitions occurring during the early career stage. The dashed lines in panels (a), (c) mark the top and bottom tertiles of the distribution of job transitions by the employment-size ratio, while the dashed lines in panels (b) and (d) indicate the top and bottom tertiles of the distribution based on relative productivity between destination and origin firms.

Figure 10

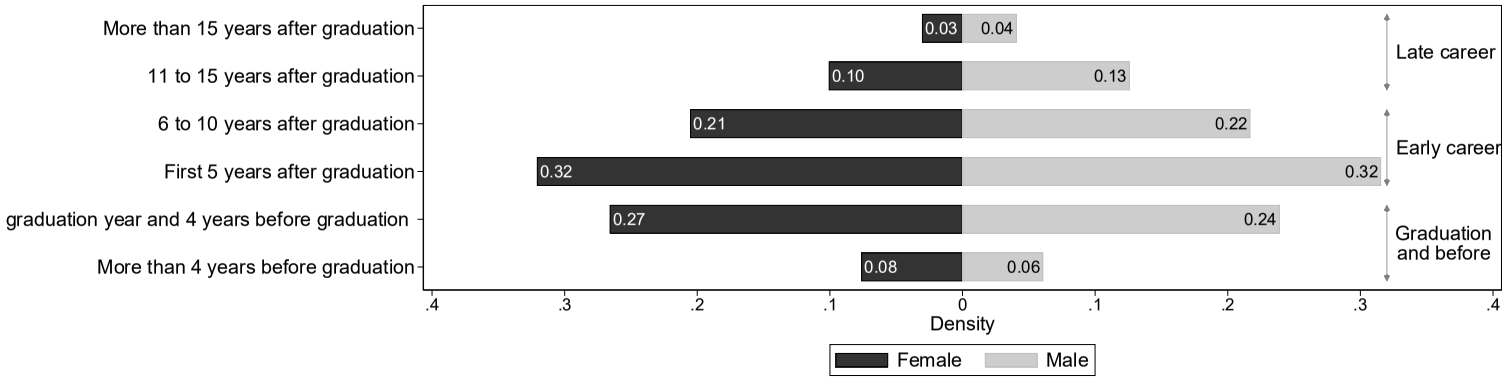
Ownership similarity and job transition to large and productive firms in early career stage



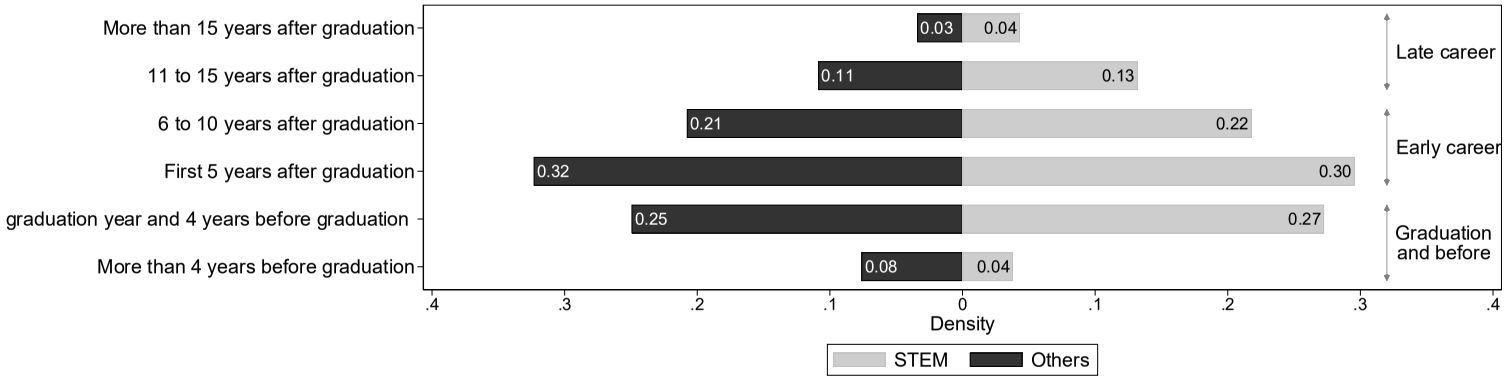
The figure shows the differential effect of higher ownership similarity across company pairs and sheds light on the impact on the likelihood of sorting into large and productive firms during the early stages of a career.Coefficient (1) reports the baseline effect across job transitions between all company pairs. Coefficients (2)-(4) reports the effect when I restrict the sample to the top, middle, and bottom tertiles of company pairs based on the size ratio of the destination to the origin employer. The ratio is calculated using each firm's number of employees in the year when the transition occurred. Coefficient (5)-(7) presents the corresponding effect when I restrict the sample to the top, middle, and bottom tertiles of company pairs based on the productivity ratio of the destination to origin firm in the year when the transition occurred. Early career stage defined the first 10 years after the bachelor graduation. Gray lines denote 95% confidence intervals. The figure visualizes the results of Table (6)

Figure 11

(a)
Job transitions by career stages and gender



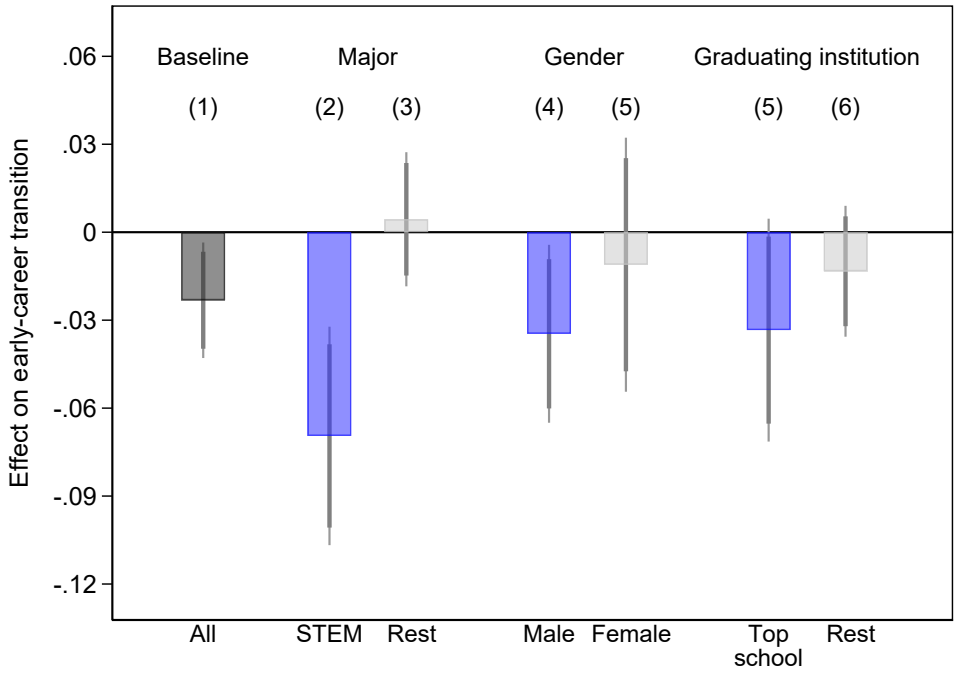
(b)
Job transitions by career stages and field of study



The figure illustrates how job transitions between S&P 500 companies from 2006 to 2015 are distributed across different career stages, with panel (a) comparing female and male individuals, and panel (b) comparing individuals with and without a bachelor's degree in STEM fields.

Figure 12

Ownership similarity, employee characteristics, and early career job transition



The figure shows the effect of higher ownership similarity on the likelihood of job transitions during the early career stage, and how varies by employee characteristics. Coefficient (1) reports the baseline effect across all employees. Coefficients (2) and (3) split the sample by field of study, with (2) capturing transitions of employees holding bachelor's degrees in STEM fields and (3) capturing those with other degrees. Coefficients (4) and (5) distinguish by gender, reporting results for male and female employees, respectively. Finally, Coefficients (6) and (7) split the sample by graduating institution, comparing employees with bachelor's degrees from top 100 universities, according to the U.S. News National University Rankings, to those from other institutions. Early career stage defined the first 10 years after the bachelor graduation. Gray lines denote 95% confidence intervals. The figure visualizes the results of Tables (7), (8), and (10)

Table 1

Summary statistics

	Obs	Mean	Median	Std.Dev.	Min	Max
Panel A: Company pairs						
Pr(Job transition)	36782	0.754	1.000	0.431	0.000	1.000
log(Job transition)	27740	1.135	1.099	1.020	0.000	8.103
χ	36782	0.689	0.711	0.148	0.083	0.900
$\Delta\chi$	36646	0.016	0.011	0.018	-0.006	0.105
Panel B: Employee composition						
Career stages						
Graduate year and before	199569	0.326	0.000	0.469	0.000	1.000
Early career	199569	0.526	1.000	0.499	0.000	1.000
Late career	199569	0.147	0.000	0.354	0.000	1.000
Education & gender						
Bachelor in STEM field	199569	0.206	0.000	0.405	0.000	1.000
Bachelor from top school	199569	0.277	0.000	0.447	0.000	1.000
Female	116180	0.399	0.000	0.490	0.000	1.000
Panel C: Employer composition						
log(TFP) of origin firm	132988	1.317	1.251	0.811	-0.188	3.526
log(TFP) of destination firm	136052	1.467	1.422	0.916	-0.242	3.638
TFP of origin to destination firm	102093	1.921	1.001	2.916	0.054	18.388
Share of transition to more productive firms	102093	0.507	1.000	0.500	0.000	1.000
Employees of origin firm (millions)	195475	0.236	0.140	0.389	0.003	2.200
Employees of destination firm (millions)	195629	0.167	0.103	0.265	0.004	2.100
Employees of of origin to destination firm	191695	1.851	0.783	4.182	0.022	36.971
Share of transitions to larger firms	191695	0.409	0.000	0.492	0.000	1.000

Panel A, presents the summary statistics on aggregate job transitions between company pairs, along with the corresponding predicted and actual impact of the merger.Note that Pr(Job transition) is a dummy variable that takes the value of 1 if there is any transition from firm i to firm j in year t, and zero otherwise. log(Job transition) is the logarithm of the number of job transitions from firm i to firm j in year t. χ is a ownership similarity between firm i and firm j in year t. $\Delta\chi$, the "Impact of Merger" is a continuous variable measuring the predicted increase in ownership similarity after the merger. The predicted change in ownership similarity is calculated in the last quarter of 2008, prior to the merger. Implied changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes in 2008Q4 and the actual ownership similarities in 2008Q4. Panel B and C reports summary statistics on the composition of the job transitions between S&P 500 companies in our dataset. "Graduate year and before" is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. "Early career" is a dummy equals one if the transition occurs within the first ten years after bachelor's graduation. Late career is dummy variable equals one if the transition happens more than ten years after graduation. Female is a dummy that is inferred from individuals' names. following Peri et al. (2015), I define STEM fields based on the classification used by the U.S. Department of Homeland Security to determine eligibility for the F-1 Optional Practical Training (OPT) extension. Top school are the top 100 institutions according to the U.S. News National University Rankings. log(TFP) estimated from a Cobb–Douglas production function using a control function approach, similar to De Loecker et al. (2020) and Díez et al. (2021).

Table 2

Baseline regressions: Effect of ownership similarity on job mobility

	(1) Ownership similarity b/se	(2) Log(Job transitions) b/se	(3) Pr(Job transitions) b/se	(4) Number of Job transitions b/se
Merger Impact×				
Post merger (year≻ 2008)	0.028***	-0.086***	-0.012	-0.116***
	(0.004)	(0.026)	(0.013)	(0.044)
Company pairs FE	Yes	Yes	Yes	Yes
Origin sector × year FE	Yes	Yes	Yes	Yes
Destiniation sector × year FE	Yes	Yes	Yes	Yes
Observations	36588	27549	36588	36524

Note: The dependent variables in columns (1) is the average cosine similarity between the ownership structure of two firms during the year t. The dependent variable in columns (2) is the logarithm of the number of job transitions from origin firm i to destination firm j in year t. The dependent variable in columns (3) is a dummy variable that takes the value of 1 if there is any transition from origin firm i to destination firm j, and zero otherwise. The dependent variable in columns (4) is the number of job transitions from origin firm i to destination firm j. "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The coefficients in columns (1), (2), and (3) are estimated using OLS regressions. The reported coefficients in column (4) is estimated using Poisson QMLE. . The The coefficients in columns (2), (3), (5), and (6) are estimated using OLS regressions.To facilitate interpretation, I normalized the continuous variable for the "Impact of Merger" in the second row by its standard deviation. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 3

Alternative sample: Effect of ownership similarity on job mobility

	Number of job transitions prior to merger				
	≥ 0	≥ 2	≥ 3	≥ 4	≥ 6
			baseline		
Dependent variable: Log(job transitions)	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Merger Impact×					
Post merger (year$\succ$ 2008)	-0.042***	-0.066***	-0.086***	-0.103***	-0.123***
	(0.016)	(0.021)	(0.026)	(0.031)	(0.040)
Company pairs FE	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	60908	36034	27549	21883	14945

Note: The dependent variable in all columns is the logarithm of job transitions from firm i to firm j in quarter t. The "Impact of Merger" variable is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated in the last quarter of 2008, prior to the merger. Implied changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes in 2008Q4 and the actual ownership similarities in 2008Q4. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 4: IV regressions

	(1) Log(Job transitions)	(2) Pr(Job transitions)	(3) Number of Job transitions	Log(Job transitions)	Pr(Job transitions)	Number of Job transitions
	b/se	b/se	b/se	b/se	b/se	b/se
Panel A : Second-stage estimation						
Ownership similarity	-2.945***	-0.542	-4.403***	-1.991***	-0.710***	-3.341***
	(1.006)	(0.443)	(1.360)	(0.555)	(0.268)	(0.829)
Panel B: First-stage estimation, Dependent variable: Ownership similarity						
Merger Impact: Top tertile of $\Delta\chi$						
Merger Impact×Post merger	0.030***	0.029***	0.029***			
	(0.005)	(0.004)	(0.004)			
Merger Impact: $\Delta\chi$						
Merger Impact×Post merger				1.102***	0.986***	0.986***
				(0.100)	(0.095)	(0.095)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27704	36765	36765	27704	36765	36765
F-test	37.50	42.15	42.15	120.18	108.19	108.19

Note: The dependent variable in columns (1) and (4) is the logarithm of the number of job transitions from firm i to firm j in quarter t. The dependent variable in columns (2) and (5) is a dummy variable that takes the value of 1 if there is any transition from firm i to firm j in quarter t, and zero otherwise. The dependent variable in columns (3) and (6) is the number of job transitions from firm i to firm j in quarter t. The reported coefficients in columns (3) and (6) are estimated using Poisson QMLE and standard errors are bootstrapped using 500 replications.In In columns (4) to (6), The "Impact of Merger" variable a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. In columns (4) to (6), The "Impact of Merger" variable is a continuous variable measuring the predicted increase in ownership similarity after the merger. The predicted change in ownership similarity is calculated in the last quarter of 2008, prior to the merger. Implied changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes in 2008Q4 and the actual ownership similarities in 2008Q4. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 5: Ownership similarity and job mobility across career stages

	Main			First bachelor degree			Exc short degrees			First bachelor exc short degrees		
	(1) Graduation and before b/se	(2) Early career b/se	(3) Late career b/se	(4) Graduation and before b/se	(5) Early career b/se	(6) Late career b/se	(7) Graduation and before b/se	(8) Early career b/se	(9) Late career b/se	(10) Graduation and before b/se	(11) Early career b/se	(12) Late career b/se
Merger Impact×												
Post merger (year≻ 2008)	0.007	-0.023**	0.016**	0.006	-0.020**	0.014*	0.012	-0.027***	0.015**	0.010	-0.024**	0.014**
	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)	(0.007)	(0.009)	(0.010)	(0.007)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197910	197910	197910	197910	197910	197910	197910	197910	197910	197910	197910	197910

Note: The dependent variable in columns (1), (4), (7), and (10) is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. In columns (2), (5), (8), and (11), the dependent variable equals one if the transition occurs within the first ten years after bachelor's graduation. In columns (3), (6), (9), and (12), the dependent variable equals one if the transition happens more than ten years after graduation. Columns (1)–(3) present our baseline specification, where career stages are defined based on the timing of the last bachelor's degree. Columns (4)–(6) use instead the timing of the first bachelor's degree to define the career stages. Columns (7)–(9) use the last bachelor's degree ignoring degrees that are less than two years. Columns (10)–(12) uses the first-degree timing ignoring the bachelor degrees that are less than two years . The sample includes all job transitions between S&P 500 firms in the baseline regressions in table (2). "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 6: Ownership similarity and sorting in early career stage

	All	Tertiles of company-pairs according to					
	baseline	Size ratio of destination to origin employer			Productivity ratio of destination to origin employer		
		Top	Middle	Bottom	Top	Middle	Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Merger Impact×							
Post merger (year≻ 2008)	-0.023**	-0.060***	-0.023	-0.017	-0.103***	-0.021	-0.007
	(0.010)	(0.023)	(0.019)	(0.018)	(0.034)	(0.020)	(0.032)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197910	42403	100491	47318	22368	58720	20720

The table reports the differential effect of higher ownership similarity across company pairs and sheds light on the impact on the likelihood of sorting into large and productive firms during the early stages of a career. Across all columns, the dependent variable equals one if the job transition occurs during the early career stage, defined as within the first ten years after completing a bachelor's degree. Column (1) includes all job transitions and corresponds to our baseline result in column (2) of Table 5. Columns (2)–(4) restrict the sample to the top, middle, and bottom tertiles of company pairs based on the size ratio of the destination to the origin employer. The ratio is calculated using each firm's number of employees in the year when the transition occurred. Column (5)-(7) restrict the sample to the top, middle, and bottom tertiles of company pairs based on the productivity ratio of the destination to origin firm in the year when the transition occurred. Productivity is measured by TFP and estimated from a Cobb–Douglas production function using a control function approach, similar to De Loecker et al. (2020) and Díez et al. (2021). Early career stage defined the first 10 years after the bachelor graduation. The "Impact of Merger" variable a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 7: Ownership similarity and job mobility by career stage and gender

	All	Female			Male		
	(1) Female b/se	(2) Graduation and before b/se	(3) Early career b/se	(4) Late career b/se	(5) Graduation and before b/se	(6) Early career b/se	(7) Late career b/se
Merger Impact×							
Post merger (year≻ 2008)	-0.008	0.009	-0.011	0.002	0.002	-0.035**	0.032***
	(0.012)	(0.021)	(0.022)	(0.013)	(0.014)	(0.015)	(0.011)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115100	45466	45466	45466	68874	68874	68874

Note: The dependent variable in column (1) is a binary indicator equal to 1 if the job transition is carried out by a female individual, and 0 if it is carried out by a male individual. The dependent variable in columns (2) and (5) is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. In columns (3) and (6), the dependent variable equals one if the transition occurs within the first ten years after bachelor's graduation. In columns (4), (7), the dependent variable equals one if the transition happens more than ten years after graduation. The sample in column (1) includes all job transitions between S&P 500 firms used in the baseline regressions reported in Table (2), for which gender can be inferred from individuals' names. Columns (2)–(4) present results for the subsample of female individuals, while columns (5)–(7) correspond to the subsample of male individuals. "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 8: Ownership similarity and job mobility by career stage and field of study

	All	STEM			Others		
	(1) STEM b/se	(2) Graduation and before b/se	(3) Early career b/se	(4) Late career b/se	(5) Graduation and before b/se	(6) Early career b/se	(7) Late career b/se
Merger Impact× Post merger (year≻ 2008)	-0.004	0.024	-0.069***	0.045***	-0.006	0.004	0.002
	(0.008)	(0.017)	(0.019)	(0.014)	(0.011)	(0.012)	(0.008)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197910	40355	40355	40355	156860	156860	156860

Note: The dependent variable in column (1) is a binary indicator equal to 1 if the job transition is carried out by a individual with bachelor degree in STEM fields, and 0 otherwise. Following Peri et al. (2015), I define STEM fields based on the classification used by the U.S. Department of Homeland Security to determine eligibility for the F-1 Optional Practical Training (OPT) extension. The dependent variable in columns (2) and (5) is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. In columns (3) and (6), the dependent variable equals one if the transition occurs within the first ten years after bachelor's graduation. In columns (4), (7), the dependent variable equals one if the transition happens more than ten years after graduation. Columns (2)–(4) present results for the subsample of individuals with a bachelor's degree in STEM fields, while columns (5)–(7) present results for those with a non-STEM bachelor's degree. "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 9: Ownership similarity and job mobility by career stage, field of study and gender

	All	STEM			Others		
	(1) STEM	(2) Graduation and before	(3) Early career	(4) Late career	(5) Graduation and before	(6) Early career	(7) Late career
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Male	0.076***	-0.013	-0.017*	0.031***	-0.027***	0.007	0.020***
	(0.005)	(0.009)	(0.009)	(0.008)	(0.006)	(0.004)	(0.005)
Merger Impact×							
Post merger (year≻ 2008)	0.004	0.037	-0.089***	0.052**	-0.010	0.011	-0.000
	(0.012)	(0.031)	(0.034)	(0.023)	(0.016)	(0.017)	(0.013)
Merger Impact×							
Post merger (year≻ 2008)×							
Male	-0.009	-0.019	0.019	0.000	-0.001	-0.003	0.004
	(0.012)	(0.027)	(0.030)	(0.021)	(0.011)	(0.017)	(0.017)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115100	23324	23324	23324	90763	90763	90763

Note: The dependent variable in column (1) is a binary indicator equal to 1 if the job transition is carried out by a individual with bachelor degree in STEM fields, and 0 otherwise. Following Peri et al. (2015), I define STEM fields based on the classification used by the U.S. Department of Homeland Security to determine eligibility for the F-1 Optional Practical Training (OPT) extension. The dependent variable in columns (2) and (5) is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. In columns (3) and (6), the dependent variable equals one if the transition occurs within the first ten years after bachelor's graduation. In columns (4), (7), the dependent variable equals one if the transition happens more than ten years after graduation. Columns (2)–(4) present results for the subsample of individuals with a bachelor's degree in STEM fields, while columns (5)–(7) present results for those with a non-STEM bachelor's degree. Male is a binary indicator equal to 1 if the job transition is carried out by a male individual, and 0 if it is carried out by a female individual. "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

Table 10: Ownership similarity and job mobility by career stage and graduating institution

	All	Top School			Others		
	(1) Top school b/se	(2) Graduation and before b/se	(3) Early career b/se	(4) Late career b/se	(5) Graduation and before b/se	(6) Early career b/se	(7) Late career b/se
Merger Impact×							
Post merger (year≻ 2008)	-0.004	0.020	-0.033*	0.013	0.000	-0.013	0.013*
	(0.008)	(0.017)	(0.019)	(0.016)	(0.011)	(0.011)	(0.008)
Company pairs FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destiniation sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	197910	54040	54040	54040	143319	143319	143319

Note: The dependent variable in column (1) is a binary indicator equal to 1 if the job transition is carried out by a individual with bachelor degree from top school, and 0 otherwise. Top school are the top 100 institutions according to the U.S. News National University Rankings. The dependent variable in columns (2) and (5) is a dummy equal to one if the job transition occurs in the bachelor's graduation year or earlier. In columns (3) and (6), the dependent variable equals one if the transition occurs within the first ten years after bachelor's graduation. In columns (4), (7), the dependent variable equals one if the transition happens more than ten years after graduation. Columns (2)–(4) present results for the subsample of individuals with a bachelor's degree from top school, while columns (5)–(7) present results for those with a bachelor's degree from other institutions. "Impact of Merger" is a dummy variable that takes the value of 1 if the firm pairs are in the top tertile of predicted increase in ownership similarity after the BlackRock-BGI merger, and zero otherwise. The predicted change in ownership similarity is calculated at the end of 2008, prior to the merger. Predicted changes reflect the difference between counterfactual ownership similarities when consolidating BlackRock and BGI ownership stakes and the actual ownership similarities. The standard errors are clustered at the firm-pairs. *** and ** denote statistical significance at the 1, 5 percent levels respectively.

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