College Alumni Networks and Mobility Across Local Labor Markets*

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(Job Market Paper)

November 3, 2025

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Abstract

We quantify the impact of alumni networks on the geographic mobility of job seekers for nearly 1,400 US colleges and universities. We use detailed employment and education information on LinkedIn users to isolate college-educated workers who faced an exogenous job separation in a mass layoff or firm closure. Using a nested logit model of location choice, we compare the migration decisions of job seekers who were displaced in the same city and who attended different but similar and geographically proximate universities. We find that a 1% increase in the number of co-alumni in the city of displacement increases a job seeker's odds of staying there by 0.4%. Conditional on moving, a 1% increase in a potential destination's number of co-alumni increases the odds of choosing that city over another by 0.9%. Co-alumni may both impact job search and provide local amenities. Using data on the presence or absence of co-alumni at new jobs, we conclude that the job search channel is particularly important. Co-alumni from the same or neighboring graduating class have much larger impacts on location choice, indicating true network effects rather than idiosyncratic matches between alumni of certain colleges and jobs in certain cities. We also find strong impacts of having more local co-alumni who work in the same industry.

*Richard would like to thank his advisors David Card, Enrico Moretti, and Jesse Rothstein for their invaluable support and guidance. We additionally thank Pat Kline, Maisy Wong, Ben Keys and many others at UC Berkeley, Wharton and the All-California Labor Economics Conference for their helpful comments and suggestions. We are incredibly grateful to Emily Fan, Ari Pereira Gomes, Stephen Liu and Rocky Zhao for outstanding research assistance. This project benefitted from financial support provided by the Institute for Research on Labor and Employment at UC Berkeley. Contact: Richard Jin, UC Berkeley (richjin@berkeley.edu); Heidi Artigue, The Wharton School, University of Pennsylvania (hartigue@wharton.upenn.edu).

1 Introduction

An individual's choice of where to live and work affects every aspect of their life. Places vary in both their economic opportunities and the local amenities that they provide to workers, and the co-location of workers gives rise to agglomeration economies that benefit both workers and the firms that employ them (Glaeser and Gottlieb 2009). The location choices of college-educated workers are particularly policy relevant, given evidence of the externalities from a better-educated local workforce (Moretti 2004b; Shapiro 2006) and the rising concentration of these workers in relatively few cities, both in the US (Moretti 2012; Diamond and Gaubert 2022) and other high-income countries (Iammarino et al. 2019). These economic consequences are magnified by the fact that college graduates are highly mobile across local labor markets (Molloy et al. 2011; Jia et al. 2023).

College alumni networks are an obvious mechanism that help *push* and *pull* the graduates from a particular college to a particular set of cities. Nearly all college graduates have expansive networks of co-alumni in many local labor markets, with some cities having tens of thousands of alumni from a single school. Such networks arguably play an important role in job search. Indeed, the online platform LinkedIn shows job seekers the employers of not only direct contacts but also other alumni from their *alma maters* — presumably because personal contacts can aid in the job matching process. Alumni networks can also help employers learn about the graduates from particular schools, improving the precision of signals in the matching process (Dustmann et al. 2016). Although there is a lot of work on how interpersonal networks affect job search,[1] and job search is by far the most commonly-stated reason for moving (Jia et al. 2023), there is surprisingly little evidence on how interpersonal networks of any kind, and alumni networks in particular, directly impact location choice.

In addition to providing information that can be helpful in the job search and matching process, the presence of local co-alumni can directly impact the value of a particular city if graduates value social interactions with their college friends and the friends of their friends. Many alumni networks also have local branches that organize social events, reinforcing the strength of alumni connections and promoting local ties.

This paper provides the first causal evidence on how local college alumni networks affect mobility and hiring for workers across the US. Using LinkedIn data, we identify nearly 20,000 college graduates who are observed on a job in the period 2010-2018 and subsequently are displaced from a mass layoff or firm closure. We follow these workers in the year after dis-

[1] Existing work on network effects looks at neighbors (Bayer, Ross, and Topa 2008; Hellerstein, Kutzbach, and Neumark 2019), family members (Kramarz and Skans 2014), and classmates (Kramarz and Thesmar 2013; Zhu 2022; Eliason et al. 2023; Ost et al. 2024).

placement and observe whether they remain in the same original metro area (their "origin") or move to a new metro area (a new "destination"). We model the decision of both *whether* to move and *where* to move using a nested logit structure in which a displaced job seeker first chooses to stay in the origin or leave, and then conditional on leaving, chooses among all possible new destinations. Accordingly, we estimate both the impact of origin alumni network size on the probability of remaining in the origin after a displacement event, and the impact of destination alumni network size on the choice over alternative cities. In our framework, local alumni networks increase the number of job leads for local opportunities and also provide potential local amenities. We highlight the importance of the job search channel by distinguishing between the probability of re-employment at local firms that employ other alumni from the same college, and at firms in destination cities with and without coworkers from the same college.

Our approach overcomes several substantial challenges to understanding how college networks impact the labor market. First, we observe a panel of workers with detailed information on both their *alma maters* and their locations and the identities of their employers over time. In the US, administrative data typically has either individual education histories or worker locations obtained from employment histories, but not both.[2] As a result, data availability has hindered research on the impacts of networks on geographic mobility.

Second, even with specialized data, the researcher must contend with several threats to identification of the effects of local alumni network size. Most prominently, worker location choice is endogenous. Workers who voluntarily leave their firms to change jobs and/or locations are not randomly selected. We isolate a sample of workers who were exogenously separated from their jobs and consequently had to make a new decision about whether to remain in their city of displacement or move to a new location.

Next, one must contend with the endogeneity of college alumni networks. It is natural to expect that graduates from the same institution could have correlated preferences for location characteristics. For example, NYU graduates may tend to favor large cities, or UCSD graduates coastal cities. If so, we would expect to see workers move to places with a large alumni network, even in the absence of any treatment effect. We address concerns about correlated preferences among alumni by leveraging LinkedIn's broad coverage of college-educated US workers to facilitate narrow worker comparisons. To identify and estimate the effect of alumni network size in the origin on the probability of finding re-employment in the origin, we compare job seekers who were displaced in the same city and went to observably similar schools in the same area, but who have differently-sized alumni networks in their

[2] Some countries outside of the US have administrative datasets that can link education, employment and location histories, but have insufficiently many local labor markets to study geographic mobility.

city of work at the time of displacement. For example, we compare two workers who were both laid off due to mass layoffs in Denver, CO, one of whom attended Williams College and the other Amherst College, both highly selective small liberal arts colleges located in rural Massachusetts that also have similar distributions of majors. Our identifying assumption is that any unobserved location preferences are absorbed by a combination of fixed effects for the city of displacement, the location of the *alma mater*, and the type of *alma mater* as defined by size, selectivity and other institutional characteristics.

Another source of endogeneity in alumni networks is the possibility of idiosyncratic match effects between the alumni of certain colleges and the jobs in a certain city. We address this concern in several ways. First, we further refine our comparisons between displaced workers in the same location who attended different but similar and geographically adjacent schools. Specifically, we additionally compare such workers who were also displaced in the same industry or even the same firm. Next, we show that estimated effects are largest for networks of alumni from the same or neighboring cohorts — groups of students with whom a job seeker is most likely to have interacted. We also directly absorb match effects across all city-school pairs in extended analyses of the impact of more granular co-alumni networks on location choice. Finally, we implement a control function approach using an instrumental variable for a school's local alumni network size based on a combination of the historical share of in-state students at the college and the distance from the college to a given city.

Our first key finding is that an increase in the size of a worker's local college alumni network decreases their likelihood of relocating to a different local labor market one year after displacement. Specifically, increasing the network size in the city of displacement by 1% (the average number of co-alumni in the city of displacement is approximately 17,000) increases a worker's odds of staying by 0.39%. This result is driven primarily by increases in the probability of remaining in the city of displacement and finding a new job at a firm that employs co-alumni: increasing the local college alumni network size by 1% increases a displaced worker's odds of staying in the same local labor market and finding re-employment at a firm with at least one co-alumni by an even larger 0.55%. The latter effect is surprising given that for the average job seeker in our sample, only 1 in 15 firms in the displacement city have a co-alum. The effects are also larger for older job seekers, who are generally less likely to move than younger job seekers.

We then investigate whether, conditional on moving to a new destination, an increase in a potential destination's alumni network size increases the job seeker's odds of choosing that destination as their place of work and residence. We derive and estimate a specification similar to a "gravity equation" that relates the number of job seekers from a school who are displaced in a particular origin and choose a specific destination to the number of co-alumni in each destination, as well as other determinants of job seekers' utility in each destination. Our identifying assumption is that, outside of the city of displacement, correlated preferences for distant locations do not differ among the alumni of a sufficiently narrowly defined set of geographically adjacent schools. For instance, we assume that Williams and Amherst alumni who are displaced in Denver do not meaningfully differ in their latent preferences for living and working in Dallas, but allow arbitrary differences in preferences between Williams alumni and UT Austin alumni.

We test for relevant threats to identification to strengthen the credibility of our results. Our results are robust to incorporating location-varying heterogeneity in demographic characteristics in our model, which accounts for correlated preferences in a richer way. We rule out labor demand factors common to job seekers of the same major, industry, or firm, as well as locational preferences for and return migration to home locations. We estimate that, conditional on moving, a 1% increase in the number of co-alumni working in an alternative local labor market increases the odds of a displaced job seeker also choosing to work and live there, relative to any other place, by 0.91%. Thus, an increase in a destination's alumni network size substantially improves a job seeker's likelihood of locating there.

We also show that destination network size has a larger impact on the joint flow of job seekers to the destination and to firms with other co-alumni, than on the joint flow of job seekers to the destination and to firms without other co-alumni. This finding is consistent with local alumni networks impacting geographic mobility in large part through their assistance in job finding. We also show that conditional on leaving the city of displacement, destination choices among younger job seekers are far more responsive than those of their older counterparts to differences in the alumni network sizes in alternative cities. Whereas older job seekers may have stronger networks across different cities that originated outside of college, younger job seekers are less likely to have built these additional networks and more likely to rely on college alumni networks.

To lend further credibility to our estimates, we construct instrumental variables for origin and destination alumni network size based on the interaction between a school's historical share of in-state students (calculated in 1972) and the inverse distance between the school and different cities. This approach isolates variation in network size that comes from historically driven differences in the "home bias" of graduates from a given school, combined with relative distance to different cities. We use these instrumental variables in a control function approach within our nested logit model to re-estimate the impacts of local alumni network size on both out-mobility and directed migration. The resulting estimates of the effect of network size are very similar to our baseline estimates, and show significant effects of alumni network size on the decision to stay in or leave the city of displacement, and on the choice of alternative destinations for those who move.

Finally, we examine additional mechanisms by which local alumni networks affect location choice. We find that same- and neighboring-cohort alumni networks, which are more likely to consist of direct peers, influence location choice more strongly than the vastly larger networks of co-alumni from distant cohorts with whom a job seeker did not overlap during school. We also show that industry-specific human capital can affect job seekers' geographic mobility. If workers have accrued significant experience in a particular industry, then switching industries can be costly (Parent 2000). Indeed, we find that displaced job seekers are more likely to locate in cities with larger networks of co-alumni who work in their industry of displacement, consistent with Moretti and Yi (2025).

In these latter analyses, we construct extremely granular alumni networks, which allows us to absorb additional threats to identification that vary across city-school pairs in our baseline analyses. Altogether, we show that local college alumni networks, which are spread across local labor markets and are salient social networks for tens of millions of college-educated workers, have a significant impact on geographic mobility.

Our work contributes to a broad literature on interpersonal networks and labor market outcomes, which has focused on hiring as the primary outcome of interest. Previous studies have found positive effects on hiring from residential networks (Bayer, Ross and Topa 2008; Hellerstein, Kutzbach and Neumark 2019), family networks (Kramarz and Skans 2014), and educational networks (Kramarz and Thesmar 2013; Zimmerman 2019; Zhu 2022; Eliason et al. 2023). In these studies, networks facilitate hiring to a specific firm via direct referrals from known individuals.

We contribute to this literature by providing the first evidence on how interpersonal networks *jointly* affect both geographic mobility and job search. Recent work has demonstrated the impact of smaller personal networks on mobility, including from family members (Huttunen et al. 2018), cell phone contacts (Büchel et al. 2020; Blumenstock et al. 2025), birthplaces (Stuart and Taylor 2021; Buggle et al. 2023), Facebook friends (Koenen and Johnston 2024), and randomly-assigned World War II Navy shipmates (Green 2024). We link this body of work to the literature on interpersonal networks and job search. Our setting is advantageous since we have rich individual-level data on employment histories and various labor market outcomes. This information allows us to directly conceptualize geographical areas as not just places but rather as local labor markets in which large social networks actively help job seekers find re-employment. We further emphasize this role by focusing exclusively on exogenously separated job seekers who are forced to both search for a new job and potentially relocate.

Our second key contribution is to extend the scope of relevant networks far beyond individual-level connections to the entire universe of alumni. Widely used job search platforms such as LinkedIn provide information and suggestions to job seekers of firms with co-alumni who are not direct contacts. Estimated treatment effects from our networks definition also pick up signaling benefits that one's *alma mater* provides to firms. If a city has a large network of alumni from a particular school spread across many firms, and those firms in turn learn that the school's alumni are a good match, then the firms may be more likely to hire additional alumni. This channel may be particularly relevant for younger college graduates without additional networks from previous employers (Cingano and Rosolia 2012; Hensvik and Skans 2016). In this regard, we additionally contribute to a more recent literature on the impact of online networks on labor market outcomes, e.g. individual Facebook friends (Gee et al. 2017; Koenen and Johnston 2024). We study even larger online networks and provide the first evidence on how an individual's set of all co-alumni (observed online) from their *alma mater* can shape mobility.

Our focus on college alumni networks, most directly related to the aforementioned studies on educational networks' labor market impacts, also moves beyond the existing literature's firm-specific network measures, e.g. the number or share of classmates at a firm. In our setting, if job search manifests across an entire local labor market, then our treatment mechanism has a scope beyond a single firm. Our data and approach are uniquely suited to capture this phenomenon, with detailed information on educational histories and locations of over 50 million workers per year on average. We compute alumni network sizes for nearly every 4-year US college/university in each US local labor market, solidifying our study's external validity. By contrast, previous studies of firm-level educational networks are difficult to scale up to the local labor market level since they use data from settings covering a narrow set of schools and geographies (Zhu 2022; Eliason et al. 2023; Ost et al. 2024).

Altogether, our results suggest a multifaceted value of local college alumni networks for job seekers. First, the network of alumni from a displaced college-educated worker's *alma mater* in the local labor market of displacement provides insurance against displacement's negative labor market impacts by facilitating re-employment in the same local labor market. Co-alumni networks can thus shield workers from having to relocate across metros, which can entail high costs of moving (Kennan and Walker 2011). At the same time, job seekers are also drawn to large co-alumni networks in distant cities, which themselves provide consumption amenities but also facilitate re-employment in a new place.

College alumni networks' impacts on geographic mobility have direct implications for job seekers' economic well-being. Local labor markets have earnings premia that are not solely attributable to worker sorting (Card, Rothstein and Yi 2025), so that location choice directly affects earnings. Moreover, in the presence of human capital spillovers, an increased flow of college-educated workers to any particular city raises the wages of both college-educated and non-college-educated workers in the city (Moretti 2004a; Moretti 2004b). Additionally, an increased number of college graduates working in a city's tradeable sector creates "local multipliers" (Moretti 2010) by boosting employment in the non-tradeable sector.

The remainder of this paper is organized as follows. In Section 2, we describe our various data sources and present descriptive facts about the geographic variation in network sizes and characteristics of our sample of job seekers. In Section 3, we present a model of location choice, which we use to estimate treatment effects on our two margins of mobility. We address potential identification concerns in Section 4. Section 5 presents our main results. We provide additional evidence in Section 6, where we consider more granular definitions of local co-alumni networks, based on cohort and industry, and evaluate their effects on mobility. Section 7 concludes.

2 Data

We combine data on individual job histories, self-reported educational histories, and monthly flows into and out of firms. Our data covers workers in the US from 2010-2019, and is provided by the company Revelio Labs.[3] Revelio Labs creates a standardized database of employment records by collecting information from online public profiles, e.g. LinkedIn, resumes, and job postings. We use these data files to create a sample of exogenously displaced job seekers for whom we can observe educational histories and both pre- and post-displacement job locations. We now discuss relevant aspects of the data in more detail.

2.1 *Individual Job and Educational Histories*

Our empirical exercise requires observing an individual's employing firm(s), location(s) of employment, and timing of spells of employment and job search. Thus, our primary data file consists of 226 million job spells for 86 million individuals working in the US between 2010 and 2019. Each spell is linked to a worker, so that we can track workers over time. For each spell, we observe the position start date and end date (if the spell has been completed and its end recorded). For each position, we also observe occupation title, a measure of occupational seniority, predicted salary, and the state and metropolitan area of employment.[4] For 80 percent of the job spells in our sample, we also know the associated company and industry defined by 2-digit NAICS code. We restrict our data to before the COVID-19 pandemic to minimize the role of remote workers in our sample, and treat the metro area

[3] Data access via Wharton Research Data Services (WRDS): https://wrds-www.wharton.upenn.edu/

[4] Actual salaries are not observed for most of the job spells in the data. Rather, Revelio Labs generates predicted salaries based on a model that takes into account job title, firm, location and other characteristics. State and metro area are recorded for 96 percent of positions during the period we study.

of employment as the metro area of residence for all workers. We leverage the observed locations of each position and the panel structure of the data to track worker mobility across local labor markets in the US. There are 102 metropolitan areas delineated in the data, as well as 50 non-metropolitan areas, one for each state. We define each metropolitan area and state-specific non-metropolitan area as a distinct local labor market, a term we use interchangeably with city, for a total of 152 local labor markets. We define a "firm" as a company and local labor market pair. [5]

In order to measure a college-educated worker's exposure to the local college alumni network of their *alma mater(s)*, we require data on workers' individual educational histories. We obtain individual self-reported educational histories from public LinkedIn profiles and include education spells up to 2019. We capture not only younger LinkedIn users who obtained Bachelor's or advanced degrees during the latter portion of our 2010-2019 analysis time frame, but also older users who graduated prior to 2010 and remain in the labor force between 2010 and 2019.[6] When reported, the data also contains information on the degree obtained for a given education spell (71% coverage), e.g. Bachelor's, MBA, etc., and the field of degree (60% coverage).[7]

2.2 *Validation of Revelio Labs Data*

We validate the representativeness of our data for college-educated job seekers. First, we show that the nationwide industry mix for college-educated workers in the Revelio Labs data is quite similar to that observed in the American Community Survey (ACS), and remarkably so in some cities. In Figure A.1, we plot the pooled 2010-2019 2-digit NAICS shares, among prime-age college-educated workers for both the Revelio Labs data and ACS, for the entire US and Washington DC. We find a strong, positive relationship between Revelio and ACS nationwide industry shares, reassuring us of the representativeness of our data.

We also validate that the self-reported educational histories from LinkedIn that we observe accurately capture the true number of alumni from these schools. The National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS) records the number of degrees awarded in each year for each 4-year US college/university. In Figure A.2, we plot the average yearly number of degrees from 2010-2019 observed for each 4-year US college/university in the Revelio Labs data against the same number reported in IPEDS. Reassuringly, there is a strong, positive relationship between the average number of

[5] We cannot distinguish different establishments of the same firm in the same local labor market. However, this is not a first-order concern — we only study migration patterns across metro areas.

[6] We only keep prime-age workers age 22-55. Thus the earliest graduation dates are in the 1980s.

[7] For users who report spending four or more years at a Bachelor's degree-granting educational institution, but who are missing information on precise degree obtained, we impute Bachelor's degree attainment to cover well above 71% of degrees.

degrees awarded in the 2010s in our data and the IPEDS data, with a slope of approximately two-thirds. Accordingly, our data is well-suited to measure the sizes of local college alumni networks and investigate their impact on geographic mobility.

2.3 *Calculating Local College Alumni Network Size*

We combine the data on self-reported educational histories and individual job histories to measure local college alumni network size for each local labor market. For each city and year, we first identify the set of all workers who held an active position in that city and year. We then match each worker to the set of college(s) and/or universit(ies) from which they obtained any degree of a Bachelor's level or higher. For a job seeker i, we define local alumni network size based on the *alma mater* for their highest degree, denoted as s. We construct two primary network size measures for i: the log number of workers in a city, either in the year of displacement (1) or averaged across the years of displacement among job seekers from s displaced in the same city (2), who have any degree from s.[8] We use the alumni network for a worker's highest degree in order to focus on the effect of more-recent alumni networks, and to avoid contaminating the treatment effect by the choice of additional education for workers who return to education after some time in the labor force. As such, we also drop job spells that occurred prior to completion of a worker's highest degree.[9]

The main limitation we face in constructing these measures of local alumni network size is that we observe only those alumni who use LinkedIn and who have updated profile information on education history and current location. Thus, we cannot observe the in-person alumni networking effects or those manifesting through other platforms. Nevertheless, LinkedIn is the largest job-related social media platform in the US, and heavily utilized by college-educated job seekers, our population of interest.[10] Although we do not observe individual-level connections, because LinkedIn highlights for users the presence of co-alumni who are *not* individual connections, our measure of network size is closely related to what a platform user would actually observe. As an example, Figure A.3 displays a present-day snapshot of detailed information that a college-educated job seeker might see about their local alumni network when looking for jobs in a city, including the number of co-alumni at those jobs. Furthermore, for a given job seeker, these platforms may suggest new connections from the individual's college alumni network spread across myriad local labor markets.

[8] We do not calculate city-school-major network sizes given incomplete coverage of majors.

[9] However, for completeness, we also calculate network sizes based only on Bachelor's degrees, and find that our quantitative results are robust to this definition.

[10] In our data, over 80 percent of workers for whom we observe both job histories and educational degree attainment report earning a Bachelor's degree or higher, much higher than the national average. Although our data is therefore not representative of the US workforce as a whole, we are interested exclusively in the location choice of college graduates.

2.4 *Mass Layoffs and Monthly Flows Data*

We identify workers who have been exogenously separated from their jobs, either through a mass layoff or firm closure, between 2010 and 2018. We supplement our worker panel data with Revelio Labs' Workforce Dynamics data, from which we observe monthly inflows and outflows of workers for each firm-by-job-type in the database, and define a set of conditions based on drops in employment at the firm level that are consistent with a mass layoff or firm closure.[11] Because we observe the start and end dates of job spells as well as the associated firm, we characterize exogenously separated workers as those whose end dates coincide with these aforementioned declines in employment at the same firm. Our definitions of mass layoff and firm closure events closely follow those of Schmieder, Von Wachter and Heining (2023). More details can be found in section B.1 of our Data Appendix.

2.5 *Sample of Job Seekers*

Our sample of job seekers consists solely of prime-age workers, i.e. age 22-55, with at least a Bachelor's degree from a 4-year US college/university and were displaced in a mass layoff or firm closure event between 2010 and 2018. We keep the job spell of displacement as well as subsequent active job spells between 2010 and 2019. In some analyses, we also incorporate individual-level heterogeneity from Revelio Labs' data on demographic characteristics imputed from LinkedIn user names. We briefly describe this additional data in Data Appendix B.2. Our final sample consists of 17,680 displaced workers whom we observe both at displacement and post-displacement and for whom we can trace educational histories.

2.6 *Descriptive Facts about Networks and Job Seekers*

Here, we characterize both the college alumni networks that we study and our sample of displaced college-educated job seekers. We begin by documenting that the alumni networks of US colleges and universities are dispersed widely across local labor markets. In Figure 1, we show heat maps of alumni network sizes in each local labor market for three schools of different types: a) a highly selective small liberal arts college, Williams College; b) a highly selective mid-sized private university, Northwestern University; and c) a large public university, California State University (CSU) Fullerton.[12] Despite wide differences in their fundamental characteristics, all three schools share the common feature that their alumni networks are spread across local labor markets in the US. While the largest local co-alumni networks are present in the local labor markets closest to the schools themselves (e.g. New York City and Boston for Williams, Chicago for Northwestern, and Los Angeles for CSU

[11] We define a job type as a job category and job seniority level. In the Workforce Dynamics files, there are seven aggregated job categories, as well as seven distinct seniority levels.

[12] We take the yearly average (2010-2019) log number of alumni, across all degree types, working in the local labor market. We exclude non-metropolitan areas here, but include them in our main analyses.

Fullerton), these schools' alumni networks expand well beyond their home regions.

One may presume that the distributions observed in Figure 1 are simply characteristics of different school types. If this were the case, then we would expect to see similar concentrations of alumni in each local labor market between two highly similar and geographically proximate schools. Yet we find that pairs of observably comparable schools may have substantially different local alumni network sizes. In Figure 2, we show the log differences in alumni network size between each school from Figure 1 and an observably similar, geographically proximate school. Panel (a) compares Williams and Amherst College. Both schools are top-ranked liberal arts colleges nationwide, of the same size, and are located only 50 miles apart. But across the US, some cities have more alumni from one school versus the other. Cleveland has 1.4 times as many alumni from Williams as from Amherst, but neighboring Pittsburgh has more Amherst alumni. In panels (b) and (c), we find similar differences for our other examples, comparing Northwestern University to the University of Chicago and comparing CSU Fullerton to CSU Long Beach. To identify the effects of network size on geographic mobility, we use these relative differences in local network sizes between different schools of the same type and same location. In Section 4.2, we rule out endogenous sources of variation in network size and describe possible sources of exogenous variation.

We show descriptively that there is a strong correlation between the network size in a job seeker's city of displacement and their post-displacement relocation probability. We start with a simple characterization of cities with large and small networks by defining, for each school, cities in the population-weighted top and bottom terciles of local alumni network size. For a given school, the top (bottom) tercile consists of the cities with the largest (smallest) number of alumni from that school who account for the first (bottom) third of the school's nationwide alumni network. For example, New York City is in the top tercile of local alumni network size for Williams College, whereas cities with fewer alumni from Williams such as Atlanta and Phoenix are in the bottom tercile.[13]

We first compare the characteristics of job seekers in large and small local co-alumni networks, defined as top and bottom terciles of within-school local alumni network size, for our sample of workers displaced in mass layoffs or firm closures. We report summary statistics in Table 1. Our sample of college-educated job seekers is majority male majority White, and have, on average, over a decade of labor market experience. They are displaced in local labor markets with large co-alumni networks — often exceeding thousands of co-

[13]In our tercile characterization, large cities such as New York City are systematically more likely to show up in the top tercile. An alternative characterization is to define, within the same city, top and bottom terciles of network sizes based on schools. This alternative, by contrast, would systematically place small schools in the bottom tercile and large schools in the top tercile. Regardless of the tercile definition, our negative correlation between network size and relocation probability holds.

alumni. Reassuringly we see that the demographic composition of workers in large and small markets is highly similar, and even the predicted salary at displacement is similar across both groups at slightly above $80k/year. Thus, at least on observables, our sample of job seekers appears well-balanced across different network size groups.

Next, we investigate whether job seekers who are displaced in local labor markets that have larger co-alumni networks are more likely to remain in the same local labor market. In Figure 3, we plot the cumulative share of workers who have ever relocated by each quarter after displacement, separately for workers in the top and bottom terciles of local co-alumni network size for their respective *alma maters*. For completeness, we also show that the share of workers who, in quarters prior to displacement, are in a different metro than the metro of displacement is near-zero for both groups. In the post-period, however, a sizable gap in the probability of relocation emerges — within 5 quarters post-displacement, the cumulative share of workers in the bottom tercile who have relocated (40%) is twice as high as that of workers in the top tercile (20%). We then consider the full distribution of alumni network size across schools and cities. In Figure 4, we find a strong, positive relationship between the log number of alumni in the city from which a job seeker is displaced, discretized into many bins, and the average probability for each bin of staying in the same city 1 year post-displacement.

The significantly lower post-displacement relocation probabilities of job seekers displaced in cities with large versus small networks does not necessarily point to a causal relationship between network size and geographic mobility. Larger (smaller) cities such as New York City (Milwaukee) are mechanically more (less) likely to be classified as having large (small) alumni networks for all schools. If workers are generally less likely to leave big cities, then we would misattribute the gap in relocation probability to alumni network size. Another challenge in identifying the causal effect of alumni network size on geographic mobility is that workers from different schools have latent location preferences that impact their geographic mobility. Yet another factor influencing geographic mobility is the possibility that firms in specific cities have strong idiosyncratic match effects with alumni from specific schools.

3 Theoretical Framework and Empirical Strategy

3.1 *Model of Worker Location Choice*

We present a static model of location choice in which a displaced job seeker chooses a city in which to live and work in two steps, following a nested logit structure. In any city, the size of a worker's co-alumni network affects their utility from living there. This effect comes through both job-related and non-job-related channels. First, through influence on job search, a larger network increases a job seeker's utility from work. Second, workers assign social or amenity value to having more co-alumni nearby. Our model predicts that an increase in a city's alumni network size increases the probability that a worker chooses to live there. To identify network size's impact on choice probabilities, we assume equivalent structures for match effects and correlated locational preferences among alumni of sufficiently similar and geographically proximate schools.

We consider the location choice of a recently displaced job seeker as an adult, taking their choice of school as given. Among J local labor markets, workers choose one location in which to both live and work.[14] A random utility-maximizing job seeker i who graduated from school s and is displaced from their previous job in origin city o first chooses whether to stay in o or leave. If the job seeker chooses to leave, they then choose a city d among all other destinations in the set $J \setminus \{o\}$. We illustrate this location decision in Figure A.5.

In any city m, the job seeker gains utility from work y_{ms}, e.g. earnings, from local amenities B_{ms}, and from idiosyncratic taste shocks ϵ_{ioms}.[15] We assume that ϵ_{ioms} follows a generalized extreme value (GEV) distribution (McFadden 1978), which yields a nested logit framework in which the two nests are the choice to stay in o, *Stay*, and the choice over all alternatives $d \neq o$ conditional on leaving, *Leave*. Workers incur disutility from cost of living r_m, and incur moving costs C_{om}. We assume that moving costs depend on individual-specific factors, X_i', and factors that vary across origins and destinations, $\widetilde{C}_{om}$, where $\widetilde{C}_{om} \neq 0$ if and only if $m \neq o$. We allow X_i' to enter negatively in C_{oo} with parameter η — for instance, older individuals are more likely to be married and may be less likely to move, i.e. lower "cost" of staying in the origin. For all other cities $m \neq o$, X_i' enters positively in C_{om} with parameter κ.[16] The indirect utility in both the origin o and an alternative destination $d \in J \setminus \{o\}$ are sums of the observable components, denoted as V_{ioos} and V_{iods}, and the taste shocks:

$$U_{ioos} = \underbrace{y_{os} + B_{os} - r_o + X_i'\eta}_{\equiv V_{ioos}} + \epsilon_{ioos} \tag{1}$$

$$U_{iods} = \underbrace{y_{ds} + B_{ds} - r_d - X_i'\kappa - \widetilde{C}_{od}}_{\equiv V_{iods}} + \epsilon_{iods} \tag{2}$$

We allow the size of the worker's local co-alumni network in any city m to directly influence the work utility in m. After a job seeker is displaced and the previous worker-job match is destroyed, they search for a new job and seek to maximize their expected work utility from

[14] To illustrate this, in Figure A.4 we present a timeline of a job seeker's labor market history and highlight, in red, the point in time at which they are displaced and forced to re-optimize their job and location choice.

[15] Work utility y_{ms} is a reduced-form way to capture job search and matching technology, including the benefit of shorter unemployment duration, increased match probability, or better expected match quality.

[16] For simplicity, we assume these factors do not vary with the actual city of origin, but we can extend our framework to allow for such heterogeneity. We show that our results are robust to allowing characteristics to vary across all locations in Section 5.1 and Section 5.2. In all other destinations, X_i' does not impact destination choice probabilities because they are not destination-specific.

some new job. For a job seeker from school s, we allow the work utility for some job h in city m, y_{msh}, to systematically vary across cities and schools, captured by μ_{ms} as well as idiosyncratically, with an idiosyncratic match component ν_h that is i.i.d. with CDF $F(\nu_h)$:

$$y_{msh} = \mu_{ms} + \nu_h \tag{3}$$

We assume that in each city, a job seeker has a finite number of job draws proportional to the number of co-alumni from school s in that city, σ_{ms}, by a factor of $a < 1$. This assumption does not require that all draws come from jobs where co-alumni are present, and instead simply reflects the idea that job seekers are more likely to sample more jobs in a city with many co-alumni.[17] We assume that $F(\nu_h)$ is Type-1 Extreme Value (McFadden 1978), and allow for different scale parameters in the origin, ω^{Stay}, and alternative destinations, ω^{Leave}. Following Kuhn and Shen (2013), if we define y_{ms}, the job seeker's work utility in city m, as the expected value of the job with highest work utility in a sample of $a\sigma_{ms}$ draws, then :

$$y_{ms} = \begin{cases} \underbrace{\mu_{os} + \omega^{Stay}(\gamma + \log(a))}_{\equiv A_{os}} + \omega^{Stay}\log(\sigma_{os}), & \text{if } m = o \\ \underbrace{\mu_{ds} + \omega^{Leave}(\gamma + \log(a))}_{\equiv A_{ds}} + \omega^{Leave}\log(\sigma_{ds}), & \text{if } m = d \text{ where } d \in J \setminus \{o\} \end{cases}$$

where γ is Euler's constant, and the expected value of ν_h is $\omega^{Stay}\gamma$ and $\omega^{Leave}\gamma$ in the origin and alternative destinations, respectively, yielding a scaled city-school work utility A_{ms} for all m. We now have the network returns $\omega^{Stay}\log(\sigma_{os})$ and $\omega^{Leave}\log(\sigma_{ds})$, which nest many channels through which the local alumni network increases work utility in a location. First, if firms have experience with previous alumni from school s, then the network provides a signal to employers about the job seeker's productivity and facilitates better matches between job seekers in those networks and their new firms (Dustmann et al. 2016). Additionally, employees may pass along information about jobs in their respective local areas to other network members, potentially shifting the distribution of wage offers that a job seeker can receive (Calvo-Armengól and Jackson 2004; Beaman 2012). Yet another possibility is that having more employed members from the alumni network decreases the duration of job search, or that they directly influence hiring other co-alumni. We allow the aforementioned as well as other network-related mechanisms to affect y_{ms}, and measure their composite effects. To separately identify $\omega^{Stay}\log(\sigma_{os})$ from A_{os} (and $\omega^{Leave}\log(\sigma_{ds})$ from A_{ds} for $d \neq o$), we require additional structure on A_{ms}. We test several possibilities in Sections 3.2 and 3.3, and

[17] Our setup implies that in cities with no co-alumni, the job seeker has zero job draws. This rarely binds in practice, as the schools in our sample have positive alumni counts in every or almost every city.

discuss the validity and implications of our assumptions in more detail in Section 4.2.

As is the case for work utility, we also assume that for any city m, the alumni network size in m enters into amenities in a consistent manner. We decompose the city amenity into a common component experienced across schools and a school-specific component:

$$B_{ms} = B_m^{City} + \widetilde{B}_{ms} \tag{5}$$

The city amenity B_m^{City} captures a broad set of local non-wage amenities that all college graduates value equally, as in Diamond (2016). We further decompose the school-specific component $\widetilde{B}_{ms}$ into two channels, only one of which the alumni network directly enters:

$$\widetilde{B}_{ms} = g(\sigma_{ms}) + Z_{ms} \tag{6}$$

The alumni network affects local amenities via $g(\sigma_{ms})$, whereby workers value having a larger network for non job-related reasons, e.g. they like to socialize with friends and acquaintances from college. We assume that $g(\sigma_{ms})$ is log-linear with parameters ρ^{Stay} and ρ^{Leave} for each nest. That is, $g(\sigma_{os}) = \rho^{Stay}\log(\sigma_{os})$ and $g(\sigma_{ds}) = \rho^{Leave}\log(\sigma_{ds})$ if $d \neq o$. The second component of school-specific local amenities, Z_{ms}, captures correlated preferences for a location among a school's alumni. For example, Boston may be more latently attractive to workers from some college in New England than those from a school in Minneapolis. It is not possible to exactly identify Z_{ms} without further structure. We make the assumption that for sufficiently similar schools in a set K, defined as a *strata*, $Z_{ms} = Z_{mK(s)}$ for all $s \in K$. We discuss this assumption and its implications in more detail in Section 4.2.

Given our nested logit structure, we can write both the probability that worker i, displaced in city o, chooses to stay in o (denote $Pr(stay_{ios})$) and the probability, conditional on leaving o, of choosing to work in some alternative city d (denote $Pr(h_{iods}|Leave)$). Starting with $Pr(stay_{ios})$:

$$Pr(Stay_{ios}) = \frac{\exp(V_{ioos})}{\exp(V_{ioos}) + \exp(\lambda \underbrace{\log(\sum_{m=1}^{J\backslash\{o\}} \exp(\frac{V_{ioms}}{\lambda}))}_{\equiv IV_{os}})} \tag{7a}$$

$$= \frac{\exp\left[(\overbrace{\omega^{Stay} + \rho^{Stay}}^{\equiv\beta^{Stay}})\log(\sigma_{os}) + (A_{os} + Z_{os}) + (B_o^{City} - r_o) + X_i'\eta\right]}{\exp\left[(\underbrace{\omega^{Stay} + \rho^{Stay}}_{\equiv\beta^{Stay}})\log(\sigma_{os}) + (A_{os} + Z_{os}) + (B_o^{City} - r_o) + X_i'\eta\right] + \exp(\lambda IV_{os})} \tag{7b}$$

Here, $\beta^{Stay} \equiv \omega^{Stay} + \rho^{Stay}$ captures the total impact of origin network size on the probability of staying in the origin. The parameter λ, which comes from our assumption of GEV-distributed idiosyncratic taste shocks, is the measure of independence in unobserved utility across alternative destinations. We also define an essential object in our nested logit structure: IV_{os}, the inclusive value of the *Leave* nest.[18]. The inclusive value multiplied by the GEV parameter, λIV_{os}, captures the expected utility across alternative destinations in the *Leave* nest. For $Pr(h_{iods}|Leave)$, we have:

$$Pr(h_{iods}|Leave) = \frac{\exp(\frac{V_{iods}}{\lambda})}{\sum_{m=1}^{J\backslash\{o\}} \exp(\frac{V_{ioms}}{\lambda})} \tag{8a}$$

$$= \frac{\exp\left[\frac{1}{\lambda}\left(\overbrace{(\omega^{Leave} + \rho^{Leave})}^{\equiv\beta^{Leave}} \log(\sigma_{ds}) + (A_{ds} + Z_{ds}) + (B_d^{City} - r_d) - \widetilde{C}_{od}\right)\right]}{\sum_{m=1}^{J\backslash\{o\}} \exp\left[\frac{1}{\lambda}\left(\underbrace{(\omega^{Leave} + \rho^{Leave})}_{\equiv\beta^{Leave}} \log(\sigma_{ms}) + (A_{ms} + Z_{ms}) + (B_m^{City} - r_m) - \widetilde{C}_{om}\right)\right]} \tag{8b}$$

where $\frac{\beta^{Leave}}{\lambda} \equiv \frac{1}{\lambda}(\omega^{Leave} + \rho^{Leave})$ captures destination network size's impact on location choice conditional on moving. For simplicity, we denote $\widetilde{\beta}^{Leave} \equiv \frac{\beta^{Leave}}{\lambda}$ as our parameter of interest.[19] Under this framework, we study two related outcomes: 1) the job seeker's decision of whether to remain in their city of displacement (out-mobility), and 2) conditional on deciding to leave, the job seeker's location choice post-displacement (directed mobility).

We show in Appendix C.1 that if $\beta^{Stay} > 0$, then Equation 7b predicts that an increase in the number of co-alumni in the city of displacement increases the probability of staying. Likewise, we show in Appendix C.2 that if $\widetilde{\beta}^{Leave} > 0$, Equation 8b predicts that an increase in the number of co-alumni in an alternative destination increases the probability of choosing that destination, conditional on leaving.[20] We allow for this impact to come both from channels related to job search, i.e. ω^{Stay} and ω^{Leave}, or from networks' value as a local consumption amenity, i.e. ρ^{Stay} and ρ^{Leave}. Although we do not aim to quantify the relative magnitudes of these two broad channels in influencing mobility and location choice, we conduct empirical tests that provide suggestive evidence on which channel is stronger.

If $\omega^{Stay} > 0$ and $\omega^{Leave} > 0$, then we should additionally expect that increasing local co-alumni network size increases the probability of not only choosing to live and work in

[18]This term varies at the origin-school level since the observable component of indirect utility in any alternative destination does not have destination-varying individual-specific components

[19]We are able to identify both $\widetilde{\beta}^{Leave}$ and β^{Leave}, but focus on the former since it aligns more directly with our causal effect of interest. The latter, meanwhile, captures the impact on unconditional, rather than conditional, destination choice probability.

[20]Theoretically, the same condition should hold for β^{Leave}, since theoretically λ is between 0 and 1. Our estimated values of λ indeed fall in this range.

that city but also working at local firms with other co-alumni. Intuitively, the many job search-related channels that are nested in the two parameters capture mechanisms by which employed members of the local co-alumni network increase the probability that job seekers from their network are re-employed at their *incumbent firms*. For instance, co-alumni provide direct referrals and are more likely to transmit information about openings at their incumbent firms rather than other firms. A positive value of ρ^{Stay} and ρ^{Leave}, by contrast, does not deliver the same prediction, since a job seeker's amenity valuation of the local alumni network is independent of whether they work at the same firm as a co-alumni.[21]

3.2 *Impact of Local Alumni Networks on Out-mobility*

We first test the hypothesis that college-educated workers who experience exogenous job separation in a mass layoff or firm closure are more likely to remain in a local labor market with a higher concentration of alumni from their *alma mater*. From Equation 7b, we can estimate β^{Stay} in two steps. First, we obtain an estimate of the inclusive value of leaving, IV_{os}, which we denote as $\widehat{IV}_{os}$, from estimating the parameters in the conditional destination probability expression in Equation 8b. We discuss our estimation of those parameters, including $\widetilde{\beta}^{Leave}$, in Section 3.3. In the second step, we include $\widehat{IV}_{os}$ on the right-hand side and estimate β^{Stay} via a binary logit model immediately derived from Equation 7b.

To identify β^{Stay}, we must absorb the impact of origin-school work utility A_{os} and origin-specific correlated preferences among a school's alumni Z_{os}. To do so, we invoke our identifying assumption that correlated preferences $Z_{os} = Z_{oK(s)}$ for alumni of all schools s belonging to the same narrowly defined set K. As a baseline, we make a parallel assumption that $A_{os} = A_{oK(s)}$, which rules out systematic differences in origin work utility for alumni of schools within the same strata. Accordingly, we estimate the following binary logit:

$$\log\left(\frac{Pr(stay_i)}{1 - Pr(stay_i)}\right) = \alpha + \beta^{Stay}\log(\sigma_{ose_i}) + X_i'\eta + \delta_{e_i} + \phi_{oK(s)} - \lambda\widehat{IV}_{os} + \epsilon_{ios} \tag{9}$$

The logit dependent variable is an indicator for job seeker i staying in the city of displacement o 1 year post-displacement. Here, e_i refers to the year of displacement. Accordingly, $\log(\sigma_{ose_i})$ is the co-alumni network size in o in the year of displacement. We also include year fixed effects δ_{e_i}, and other individual characteristics X_i'. Our origin $\times$ strata fixed effects $\phi_{oK(s)}$ absorb the remaining components of observable indirect utility in the origin — correlated preferences $Z_{oK(s)}$, fixed work utility $A_{oK(s)}$, amenities B_o^{City}, and cost of living r_o.

To show that our results are robust to different relaxations of our baseline identifying assumptions, we additionally estimate linear probability models (LPM) as reasonable ap-

[21] Job seekers may be re-employed with other co-alumni by random chance, but we show that the rate of re-employment with co-alumni far exceeds the rate from random chance.

proximations of Equation 9 that can handle more saturated fixed effects. One relaxation to our assumption on A_{os}, the city-school component of work utility, is to include school fixed effects that absorb the possibility of schools having different relative value-added in earnings (Chetty et al. 2020; Mountjoy and Hickman 2021). Another relaxation to assuming within-strata equivalence of city-school components of work utility and correlated locational preferences is to only require this equivalence for workers in the same industry, major or firm. We explore all of these possibilities.

3.3 *Impact of Local Alumni Networks on Directed Mobility*

Next, we aim to estimate $\widetilde{\beta}^{Leave}$, which captures the impact of network size in an alternative destination on a job seeker's probability of choosing that destination, conditional on moving.[22] Using the choice probability expression in Equation 8b, it is technically possible, using absorbing fixed effects, to estimate $\widetilde{\beta}^{Leave}$ via conditional logit. However, with over 100 possible destination cities and an exhaustive set of fixed effects, it is not feasible in our setting. Instead, we recover consistent estimates of $\widetilde{\beta}^{Leave}$ using the result in Guimaraes et al. (2003) that a conditional logit framework in which the indirect utility components vary at most at the group $\times$ alternative level, where a group refers to a set of individuals, can be reformulated as a Poisson-structured gravity equation with collapsed group $\times$ alternative level data and group fixed effects.[23] In our setting, we define groups as origin-school pairs, and we estimate the following econometric specification via Poisson pseudo-maximum likelihood (PPML) for *movers only*:

$$P_{ods} = \exp(\widetilde{\beta}^{Leave} \log(\sigma_{ds}) + \phi_{od} + \phi_{os} + \phi_{dK(s)})\varepsilon_{ods} \tag{10}$$

where P_{ods} is the number of job-seeking alumni from school s who are displaced in a mass layoff or firm closure in city o and move to city d 1-year post-displacement. Within origin-school groups, we calculate co-alumni network size $\log(\sigma_{ds})$ by averaging across years of displacement. We include origin metro $\times$ school fixed effects as our group fixed effects, which absorbs the denominator of our choice probability expression in Equation 8b. We also include a set of origin metro $\times$ destination metro fixed effects ϕ_{od}, which absorb citywide amenities B_d^{City}, cost of living r_d, and moving costs $\widetilde{C}_{od}$. Invoking our identifying assumption that correlated locational preferences are the same across alumni of schools in the same strata K, i.e. $Z_{dK(s)} = Z_{ds}$, we also include destination metro $\times$ school strata fixed effects $\phi_{dK(s)}$.

[22] We can also obtain the impact on the unconditional probability, β^{Leave} itself, by first estimating $\widetilde{\beta}^{Leave}$, and then using our estimated coefficient on λ in Equation 9 to scale the estimate.

[23] Conceptually, our Poisson structure is additionally advantageous given the well-documented issues with estimating gravity equations via OLS in the presence of heteroskedasticity and zero flows (Silva and Tenreyro 2006), e.g. we observe very few moves from Seattle to Nebraska.

These fixed effects also allow for several different assumptions about the structure of the city-school component of work utility A_{ds}. If A_{ds} primarily reflects matches between firms in d with job seekers from the same narrow class of schools, which our strata capture, then $\phi_{dK(s)}$ largely absorbs A_{ds}. We also directly absorb any location-invariant city-specific and city-strata factors. And if A_{ds} also includes any location-invariant, school-specific determinants, e.g. school value-added, these are already factored out in Equation 8b. We provide an extended discussion of A_{ds} and identification in Section 4.2.

4 Identification

We aim to estimate $\beta^{Stay} \equiv \omega^{Stay} + \rho^{Stay}$, the effect of (log) alumni network size in the city of displacement on the odds of staying, as well as $\widetilde{\beta}^{Leave} \equiv \frac{1}{\lambda}(\omega^{Leave} + \rho^{Leave})$, the effect of (log) alumni network size in an alternative destination on the odds of choosing that destination, conditional on moving. These total impacts combine ω^{Stay} and ω^{Leave}, the composite effect of log alumni network size on work utility, with ρ^{Stay} and ρ^{Leave}, which governs the alumni network's impact on a city's amenity value. Identification of β^{Stay} and $\widetilde{\beta}^{Leave}$ requires overcoming two threats: endogeneity of worker location choice and endogeneity of local college alumni network size. In this section, we discuss how our empirical strategy overcomes these concerns.

4.1 *Endogeneity of Worker Location Choice*

Our theoretical framework targets the direct influence of local alumni networks on the location decisions of job seekers who were forced into actively making them. The inclusion of all job seekers would otherwise pose a selection threat to our causal channel, as workers who voluntarily change jobs and/or locations are not randomly selected. Voluntary job switchers may have unobserved characteristics that directly influence their mobility across local labor markets. This selection is problematic if these unobserved characteristics are both systematically correlated with local network size and unrelated to the network's direct influence on job search and local amenities.[24] Furthermore, if voluntary job switchers move to another city because they have already secured another job offer in that city prior to separation, then we have a potential reverse causality concern whereby mobility is predetermined.

Our exclusive focus on workers who are displaced in mass layoffs or firm closures overcomes these concerns. This sample restriction follows other studies on the impact of networks (Hellerstein et al. 2019; Ost et al. 2024) or local labor market size (Moretti and Yi 2025) on labor market outcomes. When comparing the pre-displacement raw relocation probabilities

[24] For example, voluntary job switchers may have higher unobserved ability and in turn be more inherently mobile as they preemptively seek out new job opportunities in locations with co-alumni who are more willing to hire them.

of job seekers in local labor markets with the smallest vs. largest alumni networks for their schools, as in Figure 3, we find that these probabilities are zero for both groups. This finding of no pre-displacement mobility suggests that our sample of job seekers did in fact experience displacement as a sudden event that forced a re-optimization of location choice. Thus, we find little evidence that workers select into large or small networks based on their inherent propensity to move.

4.2 *Endogeneity of Local College Alumni Network Size*

Local college alumni networks vary in size in nonrandom ways. For instance, they are larger in large metros and in metros near the college's campus. To identify β^{Stay} and $\widetilde{\beta}^{Leave}$, we must isolate the component of variation that is uncorrelated with a job seeker's preferences and mobility. We classify the endogenous determinants of location choice into labor supply factors driven by correlated preferences among alumni and labor demand factors driven by productivity matches with local firms.

On the labor supply side, we must account for unobserved location preferences. At a high level, some cities may be more attractive to college-educated job seekers in general (high B_m^{City} and/or high city-specific component of A_{ms}). Graduates from some colleges may also generally be more productive (high school-specific component of A_{ms}). Additionally, migration costs may systematically vary in ways that make some cities more or less difficult to depart from or migrate to (variation in $\widetilde{C}_{od}$). Our rich fixed effects account for all these possibilities: in models that estimate β^{Stay} we net out the impact of city-invariant school-specific work utility determinants and include city fixed effects,[25] and our directed mobility analysis includes fixed effects for origin-school pairs and origin-destination pairs. These origin-destination pair fixed effects account not only for flexible migration costs, but also allow the relative attractiveness of a destination to vary by origin.[26] For example, if residents laid off in New York City have a high average presence for large metros, we account for their increased likelihood to relocate to a city like Chicago relative to a resident laid off in Little Rock. And to whatever extent these broad location preferences vary by individual characteristics, we show that our results are robust to controlling for such preferences for each potential destination within the same gender, age bracket, and race.

The next labor supply concern is the unobserved preference structure for cities that varies by school (variation in Z_{ms}). If a school's alumni may have correlated preferences

[25] Our saturated specifications include fixed effects for origin cities interacted with fixed effects for the school strata, resulting in a flexible structure that also accounts for arbitrary productivity matches between cities and strata, which we discuss further below.

[26] If any of these factors are time-varying, then our fixed effects would not fully account for them. This threat is primarily relevant for a longer time horizon, which we minimize by restricting our time frame of analysis to only a decade that both follows the Great Recession and predates the COVID-19 Pandemic.

for locations (Manski 1993), such preferences would be positively correlated with both local network size and geographic mobility. For example, if University of California San Diego (UCSD) graduates have latent preferences for coastal living, then we would expect both a large UCSD alumni network in Los Angeles and a UCSD job seeker to be relatively likely to choose Los Angeles, even in the absence of a network treatment effect. To address this concern, we group schools into *strata*, made up of observationally very similar schools in the same location. We assume that for a school s in a strata K, $Z_{ms} = Z_{mK(s)}$. Of course, this assumption is reasonable only if the strata are quite narrowly defined. We use coarsened exact matching (CEM) to match schools by geographic proximity to each other, size, admissions rate, 75th percentile composite SAT score, and share of enrolled freshman who are in-state. We provide additional details in section B.3 of our Data Appendix.

Our sample of job seekers comes from 1,399 schools in 402 strata — an average of only 3.5 schools per strata.[27] Since schools in our strata are matched both on location and key institutional dimensions, we maximize the plausibility of our identifying assumption. For example, Williams College and Amherst College are in the same strata, along with Middlebury College, Bowdoin College, and Wesleyan University. Thus, our identification assumption would require that a Williams alum and an Amherst alum have the same average preference for living in a city such as Dallas (in practice, we interact our strata with other fixed effects to relax this assumption in multiple ways). Other examples of strata include large public universities in Arizona (University of Arizona and Arizona State University), and California State University schools in Northern California (Cal State Chico, Cal State Fresno, and Cal State Sacramento). Across strata, we allow for arbitrary variation in preferences. For example, even for two schools as similar as UCSD and San Diego State, we make no assumption on the preferences of one school's alumni compared to the other, since one school is slightly more selective and thus in a different strata.

We use these strata to account for preference correlation in several ways. In our out-mobility analysis, we estimate models with fixed effects for origin city-industry-strata triples, so that our identification assumption need hold only for workers in the same strata, city, and industry of employment. In our directed mobility analysis, we include fixed effects for destination-strata pairs, as well as fixed effects for origin-*school* pairs, so that our identification assumption need only hold for distant metros. We thus allow for different preferences, even within strata, for the metro of residence at displacement, with which the worker is presumably relatively familiar.

Our identifying assumption is not very restrictive, as it still allows for a wide range of

[27] We define 431 strata for 1,840 4-year colleges and universities, for an average size of 4.3 schools per strata, but only 1,399 schools are represented in our final estimation sample.

correlated preferences to exist without threatening identification. For instance, consider an alternative assumption that the alumni of any two schools that are located in the same geographical area, e.g. New York City, have the same latent locational preferences. We estimate models allowing for the possibility that alumni from different schools in New York City who all lost their jobs in the same city and industry may still have systematically different preferences for New York City, or elsewhere. This possibility is only ruled out if the two schools are highly similar across many dimensions.

We fortify our identifying assumption's plausibility by matching schools on the share of enrolled freshmen who are in-state. Geographic proximity to home is the top predictor of college choice (Avery et al. 2014), and standard location choice models often include proximity to home as a source of locational preference (e.g. Diamond 2016). Furthermore, nearly half of graduates from US 4-year colleges and universities reside in the nearest metro to their *alma mater* (Conzelmann et al. 2023). Within a small set of observably similar schools in the same location whose student bodies feature the same degree of geographic locality, this preference is unlikely to differ across the schools' respective alumni. To rule out any remaining confounding home bias, we estimate specifications on a restricted sample of job seekers who are displaced outside of the metro of their *alma mater* ("home metro").[28] We additionally exclude workers who return to their home metro after being displaced elsewhere.

Next, we consider potential confounding determinants of mobility on the labor demand side that vary across both cities and schools. There are two endogeneity concerns that we address. First, we have assumed that the component of work utility that is common to some city-school pair $m \times s$ can be decomposed into a city-strata component and separate city and school components, with remaining city-school match effects coming through the network size σ_{ms}. Our concern is with a potential lingering non-zero idiosyncratic match effect between city m firms and school s alumni that increases work utility y_{ms}. A positive match would both increase a graduate's probability of living in m and be positively correlated with σ_{ms}. Because job search is typically very local in nature (Manning and Petrongolo 2017), this threat is most acute in the city of displacement.[29] Thus, in our analysis of conditional destination choice, whose estimates we use to also analyze the stay vs. leave margin, we include origin $\times$ school fixed effects to directly account for the possibility of local city-school productivity matches.

We further assuage concerns about city-school match effects by showing that our results are robust to leveraging within-firm (and strata) variation in network size. We effectively

[28]We have information on high school attendance for a very small fraction of job seekers. Thus we cannot reliably infer home location based on pre-college education.

[29]On LinkedIn, job search is online and more widespread, and thus networks have a broader geographic scope. However, over 70% of displaced workers in our sample still remain in their city of displacement.

compare the location decisions of job seekers who are alums of schools in the same strata and were displaced at the *same firm*. Additionally, if firms imperfectly observe their productivity matches with schools, and instead learn about match effects through the co-alumni they employ, then these matches would constitute a treatment mechanism rather than a threat to identification, paralleling Montgomery (1991) and Dustmann et al. (2016). Finally, any residual match effects are less likely to impact our sample of job seekers with, on average, over a decade of labor market experience.[30]

The second, related concern for labor demand is that if firms in a given city and/or industry systematically prefer to hire specific majors, then differences in schools' major composition, even within a set of highly comparable schools, could lead to overstating β^{Stay} and $\widetilde{\beta}^{Leave}$. This is only a minor concern if major's productivity signal sharply attenuates with labor market experience, as in the literature on employer learning from workers' schooling. Nevertheless, to the extent that differences in school major composition manifest as differences in industrial composition of workers, we estimate models that absorb any unobserved factors varying across both cities and industries. To provide even more reassurance, we show that school strata alone explain at least 40% of the variation in school major shares for each of the six most common majors in our data.[31] And as a final check, we estimate models that directly control for factors varying across destination-major pairs and major-strata pairs.

While we cannot rule out all unobserved determinants of mobility that are correlated with local network size, we also reinforce our findings against all factors varying at the city-school pair level in Section 6.2. Here, we recalculate alumni networks within each industry of employment, and estimate models with city $\times$ school fixed effects that directly absorb the labor supply and labor demand threats discussed above.

Finally, we briefly discuss possible sources of exogenous variation in local alumni network sizes. Because we do not observe these networks forming in the years after a school opens, we are not able to empirically differentiate between possible origins, so our commentary is relatively speculative in nature. One possibility is that many geographically proximate schools

[30]Such match effects are likeliest to manifest upon graduation (such as via on-campus recruiting), as the productivity signal that schooling sends to employers quickly diminishes as workers gain experience (Altonji and Pierret 2001; Lange 2007). The comparison of schools within the same area is also significant. Although a high proportion of large firms recruit new graduates on-campus (Forsythe and Weinstein 2025), recruiting remains local in nature (Weinstein 2022). Our school strata consist of schools whose graduates draw attention from very similar sets of recruiting firms.

[31]In Table A.1, for each major recorded in the Revelio Labs data, we report the R-squared from a regression of the major's share at each school, from IPEDS in 2010, on school strata fixed effects. For each of the six most common majors, at least 40% of the variation in school major share is explained by school strata alone. For six of the eleven majors, the explained variation is at least 48%. We corroborate school strata's explanatory power by plotting a histogram of standardized residuals for each major in Figure A.6. For all majors, the standardized residuals are overwhelmingly concentrated at zero, with little spread in the distribution. Thus the average major share within strata predicts the school's major share with high accuracy for all majors.

that are highly similar today have substantially differed on key characteristics in the past, potentially resulting in student bodies with different post-graduation migration patterns. On one hand, such schools may have admitted very different students in the past — on various dimensions such as race, gender, and pre-college geography. The schools' own characteristics could have also differed, including major offerings, enrollment, or perceived quality.[32] Another possibility is idiosyncratic timing across schools in firm recruiting. Because we analyze exogenously displaced job seekers in the 2010s as opposed to fresh college graduates from earlier time periods, their location decisions are not likely to be directly impacted by the aforementioned factors other than through these factors' influence on network size.

Motivated by this intuition, we construct two instruments for local alumni network size, one each for the origin and a potential destination based on historical variation in schools' shares of in-state students. Concretely, we interact a school's in-state enrollment share in 1972 with the inverse distances between the school and the origin or a potential destination. Our instruments are $W_{os} \equiv \frac{Share_{s,1972}}{1+dist_{os}}$ and $W_{ds} \equiv \frac{Share_{s,1972}}{1+dist_{ds}}$, where $dist_{os}$ and $dist_{ds}$ are the great circle distances (in miles) between the school and the origin and destination, respectively. We employ a control function approach using these instruments, following Terza et al. (2008), to isolate arguably exogenous sources of variation in network size and re-estimate β^{Stay} and $\widetilde{\beta}^{Leave}$. We provide more details in Appendix D.1.

Our instruments are strongly positively correlated with local alumni network sizes. Intuitively, if historical alumni of a school with a high in-state enrollment share in 1972 were more likely to choose nearby cities (high inverse distance), then we would expect larger alumni networks in nearby cities in the present day. We indeed find that schools have large alumni networks in nearby cities, and our instruments isolate the variation in present-day network sizes that comes from these historical differences. Exclusion requires that differences in the 1972 in-state enrollment shares between two neighboring schools that are highly similar today, including having similar present-day in-state enrollment shares, are not systematically correlated with unobserved determinants of present-day job seekers' mobility. Because our sample of job seekers all graduated well after 1972, we minimize the plausibility that contemporaneous unobserved factors affect the location decisions of modern job seekers.

[32] Take Pomona College and Claremont McKenna College (CMC), for example. Both schools have been neck-and-neck in US News rankings during the 21st century, but in the late 1980s, which predates the graduation year of nearly all job seekers in our sample, Pomona's ranking ($\sim$ 5th) was far ahead of CMC's ($\sim$ 21st) (Source:https://andyreiter.com/datasets/). If Pomona's higher ranking drew students with higher unobserved skill who then sorted to higher-wage cities, e.g. NYC (Combes et al. 2008; Card, Rothstein and Yi 2025), then we might expect more Pomona alums than CMC alums from older cohorts, but a smaller gap for new graduates from present-day cohorts. Indeed, Pomona has 1.5 times as many alumni as CMC in NYC, yet we see a remarkable similarity between the two schools in the number of new graduates who locate in NYC — between 2016-2019, the average number of CMC alumni from the 2016-2019 graduating cohorts in New York City was 169, compared to 168 for Pomona.

As an example of our targeted variation in network size, consider Boston University and Northeastern University, two schools in the same strata with a similar in-state share in 2010. Both schools are large private research universities in Boston with near-identical rankings and similar cross-yields.[33]. But one school historically had a very local student body and the other did not. In 2010, only 27% of Northeastern University freshmen were from Massachusetts, compared to a similar 20% for Boston University. Yet in 1972, 81% of Northeastern University students were from Massachusetts, compared to only 48% for Boston University. In the present day, we see that compared to Boston University, Northeastern University has larger alumni networks in both Boston and throughout New England. While other factors, many of which we have discussed in this section, contribute to these differences in network sizes, we control for those factors and solely leverage variation that comes from these differences in home backgrounds among alumni who predate our sample of job seekers.

5 Results

5.1 *Impact of Local Alumni Network Size on Out-Mobility*

Table 2 presents our baseline second-step estimates of β^{Stay} in Equation 9. In all of our logits, we include the log co-alumni network size in the city of displacement, the inclusive value of leaving, individual controls, school controls, and fixed effects for the year of displacement.[34] To account for sampling variability in estimating the inclusive value of the *Leave* nest in our first step, we report bootstrapped standard errors based on resampling clusters at the city $\times$ school level. In column 1, we add origin fixed effects, and then in column 2, fixed effects for the origin interacted with the metro of a job seeker's *alma mater*. Our preferred specification in column 3 includes origin $\times$ school strata fixed effects. This within-strata comparison of co-alumni network size is consistent with our identifying assumption that correlated locational preferences and city-school work utility matches within a school's nationwide alumni network, the primary confounders to identifying the effect of local alumni network size, are the same across alumni networks of sufficiently similar and geographically proximate schools in the same strata.

Across all specifications, we report both our estimates of β^{Stay}, which has a direct elasticity of odds interpretation, and the associated average marginal effects.[35] We find that increasing a job seeker's alumni network size in the city of displacement by 1% yields a 0.4%

[33]Source: https://www.parchment.com/c/college/tools/college-cross-admit-comparison.php?compare=Eastern+University&with=Boston+University

[34]School controls are absorbed by any strata fixed effects, since within strata, schools are matched on observables.

[35]The interpretation of β^{Stay} is that a 1% increase in the origin alumni network size yields a β^{Stay}% increase in the odds of staying. This comes from a log-log interpretation for our logit, which relates log odds to log network size.

- 0.7% increase in the odds of staying, including a 0.4% increase in our preferred specification in column 3 (p-value < 0.01). Based on the associated average marginal effect, the magnitude of this estimate is highly similar to that of the estimated impact of local city $\times$ industry size on the relocation of displaced workers in Moretti and Yi (2025). Our estimates of λ, captured by the coefficient on the inclusive value of leaving the city of displacement, range from -0.5 to -0.37, indicating a reasonable amount of correlation between alternative destinations within the leave nest.

We also estimate more saturated models via linear approximations of our logit in Equation 9.[36] These saturated models allow for more flexible assumptions about the structure of correlated locational preferences Z_{os} and city-school components A_{os} of work utility in our model. In Table 3, in column 1 we again report our estimates from our preferred logit model, and show in column 2 that a linear probability model with the same variables yields a near-identical estimated average marginal effect. With reassurance that the linear probability model is a sensible approximation, we show that if we add school fixed effects in column 3, which absorbs any potential location-invariant school-specific components of work utility, our estimated average marginal effects remain similar in magnitude and statistically significant at the 1% level. In column 4, we instead include fully interacted origin $\times$ strata $\times$ industry of displacement fixed effects. Thus our assumption that city-school correlated preferences and work utility are captured by city-strata factors only needs to hold for workers displaced in the *same industry*. We effectively compare the out-mobility of a Williams alum who is laid off in the Finance industry in Denver to an Amherst alum who is also laid off in the Finance industry in Denver. We estimate a similar average marginal effect of 0.05 — doubling the origin network size yields a 3.5 percentage point increase in the probability of staying (p-value < 0.01), which is a 4.5% increase given the $\sim$77% baseline probability of staying.

Our finding of a strong, positive effect of origin alumni network size on the probability of staying holds when using a control function approach with an instrumental variable that isolates arguably exogenous variation in origin network size. We re-introduce the instrumental variable from Section 4.2, $W_{os} \equiv \frac{Share_{s,1972}}{1+dist_{os}}$, where $Share_{s,1972}$ is the school's in-state enrollment share in 1972 and $dist_{os}$ is the great circle distance (in miles) between the origin and school. We provide more details about our estimation procedure in Appendix D.1. The F-statistic from the first stage is 349.3, signifying the instrument's relevance. We report our two-stage residual inclusion (2SRI) estimate of β^{Stay} in column 1 of Table 4, alongside our baseline estimate in column 2. The 2SRI estimate of 0.478 is close to our baseline estimate

[36] These more saturated models do not converge when estimating logits, given the high dimensionality of fixed effects.

of 0.389, and is statistically significant at the 5% level.[37] Our estimate of λ, the dissimilarity parameter and coefficient on the inclusive value of the *Leave* nest, is -0.327 (p-value < 0.05), which is also similar to the baseline estimate of -0.367.

Thus we show that increasing the network size in a job seeker's city of displacement meaningfully increases the probability of staying in that metro. This effect combines the job search channel ω^{Stay} and amenity channel ρ^{Stay}. Descriptively, only a tiny fraction of firms in a given city have co-alumni coworkers for the average job seeker, so in the absence of a treatment effect driven by ω^{Stay}, by random chance we would expect very few job seekers to become employed at "in-network" firms. In Panel A of Figure 5, we plot a histogram of the share of firms in a job seeker's metro 1 year post-displacement across all displaced job seekers in our sample. For the vast majority of job seekers, close to 0% of local firms are in-network firms. Even for very large schools, only 10% of local firms are in-network. Nevertheless, more than 60% of workers are re-employed in-network, as shown in Panel B.

This evidence is suggestive that the job search channel is dominant in the treatment effect β^{Stay}. Formally, we re-estimate Equation 9 on two new outcomes. First, we define $1(Stay \,\&\, alum)_i$ as an indicator equal to 1 if worker i stays in metro o and is re-employed at a firm with a co-alum from school s 1-year post-displacement. Next, we define $1(Stay \,\&\, no\, alum)_i$ as an indicator equal to 1 if worker i stays in metro o and is re-employed 1-year post-displacement at a firm without any co-alumni from school s. We separately re-estimate Equation 9 as a logit with these two new dependent variables and denote the estimated coefficients on $\log(\sigma_{ose_i})$ as $\beta^{Stay,alum}$ and $\beta^{Stay,noalum}$, respectively.[38] A finding of $\beta^{Stay,alum} > \beta^{Stay,noalum}$ would strongly suggest that job search channels are dominant in the treatment effect.

The results are presented in Table 5. We re-report our baseline estimate of β^{Stay}, 0.389, in column 1. Relative to this baseline, we find that increasing the alumni network size in the city of displacement has an even more pronounced effect on the joint probability of staying and finding re-employment at a firm with another co-alumni (estimated elasticity of

[37]From bootstrapped standard errors based on 400 reps and re-sampling clusters at the origin $\times$ school level.

[38]To maintain algebraic consistency with the log-odds equation for $Pr(stay_i)$ that is our econometric specification in Equation 9, we would need an additional predictor for the log conditional probability of being re-hired at a firm with (without) a co-alumni conditional on staying in the metro of displacement. However, accurately measuring this log conditional probability would require additional modeling of the separate firm and job-level hiring outcome that is beyond the scope of this paper. As a reasonable approximation, we assume that this log conditional probability is the sum of (1) the local log co-alumni network size in the city of displacement, and (2) some function that is identical for workers in the same city o who attended geographically proximate and highly similar schools in the same strata $K(s)$. The effect of (1) is directly captured by $\beta^{Stay,alum}$ or $\beta^{Stay,noalum}$, and the effect of (2) is absorbed by city $\times$ school strata fixed effects $\phi_{oK(s)}$.

jointly staying and finding in-network re-employment, $\beta^{Stay,alum}$, of 0.55, p-value < 0.01). By contrast, in response to increasing the local alumni network size, job seekers are actually less likely (estimated $\beta^{Stay,noalum}$ of -0.34, p-value < 0.01) to stay and be re-employed without a co-alumni at their new firm. In parallel, we see that the negative impact of a higher inclusive value of the *Leave* nest on a job seeker's probability of staying comes largely from a decreased likelihood of finding new employment at local in-network firms. Meanwhile, a higher inclusive value has no discernible impact on the likelihood of staying in the city of displacement and finding employment outside of the alumni network. This result comes from the offset of two opposite-sign effects: 1) a smaller inclusive value pushes job seekers to local in-network firms and away from out-of-network firms, and 2) a larger inclusive value pushes job seekers away to other cities. Altogether, our results suggest that the local co-alumni network's positive impact on a job seeker's propensity to stay in the city of displacement comes largely from the network's value in directing job seekers to local in-network firms. This finding is perhaps unsurprising given descriptive evidence that job-related factors are the primary drivers of geographic mobility in the US (Jia et al. 2023), yet novel given a lack of focus on job search in previous studies on social networks' impact on geographic mobility.

We also test whether co-alumni network size in the origin differentially impacts out-mobility for job seekers across age groups. In addition to local networks of co-alumni, older job seekers with more labor market experience have larger networks of former colleagues who can provide both information about job opportunities (Cingano and Rosolia 2012) and signals of these job seekers' productivity to their incumbent employers (Hensvik and Skans 2016). By contrast, younger job seekers with less labor market experience may more heavily rely on their college alumni networks in the job search process. Furthermore, younger job seekers may be more likely to value local co-alumni networks as a local amenity. Friends and acquaintances can greatly impact location choice.[39] For younger job seekers, it is reasonable to expect that a higher share of their immediate social networks come from school.

Thus we might expect that a larger network in the origin would make a younger job seeker more likely to stay than an older one. Yet the baseline inter-metro mobility rate among younger individuals is far greater, indicating a higher propensity to leave (Jia et al. 2023). We repeat our empirical exercises from Table 5, which estimate the effect of co-alumni network size in the city of displacement on a job seeker's probability of staying as well as jointly staying and finding re-employment at a firm with or without a co-alumni, separately for older (35 and older) and younger workers (40 and under). We plot our estimates in Panel

[39] For instance, Koenen and Johnston (2024) document that on average, 78% of a Facebook user's friends live within 100 miles of their home CZ. Büchel et al. (2020) find that individuals strongly prefer neighborhoods where more of their phone contacts reside.

I of Figure 6.[40]

We find that the impact of co-alumni network size on a job seeker's probability of staying in the same local labor market is greater for older workers (estimated β^{Stay} of 0.621, p-value < 0.01) than for younger workers (estimated β^{Stay} of 0.338, p-value < 0.01). We also find larger estimated impacts on jointly staying in the same metro and finding re-employment at an in-network firm for older workers (estimated $\beta^{Stay,alum}$ of 0.653, p-value < 0.01) than for younger workers (estimated $\beta^{Stay,alum}$ of 0.551, p-value < 0.01), albeit with a smaller gap. Therefore, while we may have expected younger workers, who are more likely to leverage college alumni networks, to also be more likely to stay in the origin in response to an increase in network size, we cannot conclude this to be the case. Instead, we largely capture the generally higher likelihood of older workers to not move.

Our estimated treatment effect of origin network size on the probability of staying is robust to a variety of additional tests. First, while we define alumni networks based on the worker's highest degree obtained, it is possible that workers with post-Bachelor's education are nevertheless influenced by their Bachelor's alumni network. We re-estimate Equation 9 using only Bachelor's-level alumni networks and present results in Table A.4, and find that effects are slightly smaller but similar in magnitude to our baseline specification.

Additionally, one might worry that job seekers are especially attached to the metro where they went to school in a way that is not driven by the alumni network. Because the alumni network is almost always largest in this "home metro", such an attachment could bias our estimate. Therefore, in Table A.6, we exclude all workers who are displaced in the same metro in which they attended school, estimating only on workers displaced in other metros.[41] Our estimate of β^{Stay} is 0.354, which is very similar to our baseline estimate of 0.389. Thus our results are not sensitive to the widespread inclusion of job seekers who remain in their home metro and this source of potential home bias.

Beyond home bias, we show that our results are robust to controlling for location preferences that vary across individual demographic characteristics. We define 12 demographic groups based on gender (male or female), age group (22-30, 31-39, 40+), and race (white or non-white), and include destination $\times$ demographic group fixed effects in our estimation of the *Leave* nest's inclusive value and add origin $\times$ demographic group fixed effects to our baseline logit in Equation 9. We even estimate models that additionally interact these fixed effects with school strata. Thus we rule out threats as narrow as workers of the same gender, age and race as well as from the same origin or strata having common location preferences.

[40] We use slightly overlapping samples, i.e. workers between the ages of 35 and 40 are part of both groups, in order to preserve more of our sample for reliability. Conceptually, it is also unclear whether workers with more than 10 but fewer than 20 years of experience should be classified as old or young.

[41] We also estimate the inclusive value in a first step on this same sample.

Our estimates of β^{Stay}, reported in Table A.9, are larger than baseline but remain statistically significant at the 1% level.

We also alleviate concerns about idiosyncratic matches between firms in specific cities and schools. Instead of comparing job seekers who are displaced in the same industry and location and who went to schools in the same strata, we estimate a model in which we compare the out-mobility of job seekers who are alumni of schools in the same strata and were displaced from the *same firm*. Our estimates in Table A.11 are slightly larger in magnitude than our baseline estimates, and remain statistically significant at the 1% level.

We then address concerns about differences in the composition of majors across schools, even within the same strata. Concretely, instead of isolating variation in network size within the origin $\times$ industry of displacement (and additionally school strata), we isolate variation in network size within a narrow origin-major-strata cell. Thus even if similar schools differ in their production of certain majors, we only compare graduates displaced in the same city who studied the same major. We report estimates in Table A.13 that are very similar to our baseline results, with even larger estimated elasticities and average marginal effects.

Finally, we consider an alternative measure of alumni network size that does not depend on a job seeker's year of displacement. We repeat our analysis after redefining the alumni network to its average value across the 2010-2019 time period. Table A.15 shows that there is virtually no change to our estimates.

5.2 *Impact of Local Alumni Network Size on Directed Mobility*

We turn to quantifying the impact of destination alumni network size on directed migration to that destination. Table 6 presents results from estimating variations of our gravity equation in Equation 10 via PPML. Since this gravity equation yields equivalent estimates of $\widetilde{\beta}^{Leave}$ as implied by the multinomial logit framework of the *Leave* nest (Guimaraes et al. 2003), and the alumni network size is expressed in logs, we interpret our estimates of $\widetilde{\beta}^{Leave}$ as the elasticity of odds of moving to a destination city d, relative to another city, with respect to the co-alumni network size in d. In all specifications, we cluster standard errors three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels, paralleling Moretti and Wilson (2017). We also include origin $\times$ school fixed effects in all specifications, as consistent with Guimaraes et al. (2003). Our simplest specification in column 1 only includes origin $\times$ school fixed effects and destination fixed effects, and recovers large and statistically significant (at the 1% level) estimated elasticities of the odds of moving to destination city d with respect to the number of co-alumni in d. Our preferred specification in column 5 includes both destination $\times$ strata fixed effects and origin $\times$ destination fixed effects, and exactly corresponds to our econometric model in Equation 10. The former absorbs correlated locational preferences and distant city-specific work utility matches among alumni of highly similar neighboring schools, and the latter absorbs heterogeneous moving costs across origin-destination pairs. Our preferred estimate of 0.907 indicates that a 1% increase in the number of co-alumni in a destination d yields a 0.91% increase (p-value < 0.01) in the odds, conditional on moving, of moving to d over another city — a fairly substantial impact.

We can also re-frame our elasticity of odds interpretation that comes directly from our estimated $\widetilde{\beta}^{Leave}$ into a probability-based interpretation. Consider two cities d_1 and d_2, where conditional on moving, a job seeker's probability of choosing d_1 is 5% whereas their probability of choosing d_2 is 50%. Our estimated $\widetilde{\beta}^{Leave}$ of 0.91 implies that doubling the network size in d_1 raises the probability of choosing to live and work there, conditional on moving, from 5% to 9%.[42] For d_2, the city that already has a very high baseline conditional choice probability, doubling its network size raises the same probability from 50% all the way to 65%, a substantial increase.

We obtain similar estimates of $\widetilde{\beta}^{Leave}$ using a control function approach that isolates arguably exogenous variation in destination network size using the instrumental variable introduced in Section 4.2, $W_{ds} \equiv \frac{Share_{s,1972}}{1+dist_{ds}}$. Here, $Share_{s,1972}$ is the school's in-state enrollment share in 1972 and $dist_{ds}$ is the great circle distance (in miles) between the destination and school. We provide more details about our estimation procedure in Appendix D.1. We establish the instrument's relevance by noting, in column 1 of Table 7, a large F-statistic of 1,117.5 in our first stage.[43] We report our two-stage residual inclusion (2SRI) estimate of $\widetilde{\beta}^{Leave}$ in column 1 of Table 7. The estimate of 0.999 is very close to our baseline estimate of 0.907, and is statistically significant at the 1% level.[44]

Next, we evaluate the relative contributions of the job search channel and the amenity channel. That is, we evaluate the relative importance of ω^{Leave} and ρ^{Leave} to $\widetilde{\beta}^{Leave}$. Concretely, we define P^{alum}_{ods} as the number of displaced job-seeking alumni from school s who move from city o to d and are re-employed 1-year post-displacement at firms with at least one other co-alumni. Likewise, we define P^{noalum}_{ods} as the number of o to d movers from school s who are re-employed at firms without any co-alumni. We then separately re-estimate Equa-

[42] Calculation is as follows. Doubling the network size in d_1 increases the log odds of choosing d_1 by $0.91\log(2)$. This change in log odds implies a multiplicative change in odds of $\exp(0.91\log(2))$. The original odds of choosing d_1 are $\frac{0.05}{1-0.05} \approx 0.053$, meaning the new odds are $0.053\exp(0.91\log(2))$. Denoting the new conditional choice probability of d_1 as p_{d_1}, and using the odds expression where new odds are equal to $\frac{p_{d_1}}{1-p_{d_1}}$, we obtain that $p_{d_1} \approx 0.09$. We can do the same calculation for d_2.

[43] Several factors contribute to this large F-statistic. First, there are 399,131 observations in the first stage regression, at the origin $\times$ school $\times$ destination level. Additionally, college graduates tend to locate close to school, so it is unsurprising to see a strong correlation between inverse distance and network size.

[44] From bootstrapped standard errors based on 400 reps and re-sampling clusters at the origin $\times$ school level.

tion 10 with P_{ods}^{alum} and P_{ods}^{noalum} as our dependent variables, with $\widetilde{\beta}^{Leave,alum}$ and $\widetilde{\beta}^{Leave,noalum}$, the respective coefficients on the log network size in d, as the corresponding parameters of interest. While our estimate of $\widetilde{\beta}^{Leave}$ informs us about the total effect of an increase in the size of the local alumni network in d on the likelihood of moving to d, our estimate of $\widetilde{\beta}^{Leave,alum}$ provides indirect evidence on the strength of the network's job search-related channels in affecting this location choice. Likewise, a large, positive estimate of $\widetilde{\beta}^{Leave,noalum}$ would suggest that job seekers may still value local alumni networks for non job-related reasons. We re-emphasize that even for large schools with the largest networks across cities, only a small fraction of firms in those cities have co-alumni from those schools (10% average share in city of displacement for job seekers who went to schools with more than 20,000 students). Thus we do not expect that $\widetilde{\beta}^{Leave,alum}$ would exceed $\widetilde{\beta}^{Leave,noalum}$ for purely mechanical reasons.

Table 8 presents the decomposition exercise, where we re-estimate our most preferred specification of Equation 10 with the two alternate outcomes P_{ods}^{alum} and P_{ods}^{noalum} in columns 2 and 3, respectively. Similar to our out-mobility results in Section 5.1, in cities with an increase in local alumni network size, we find an increased coincidence of directed migration and in-network re-employment that is greater than the increase in mobility alone. Compared to our baseline estimate of $\widetilde{\beta}^{Leave}$% of 0.91%, which we re-report in column 1 of Table 8, in column 2 we estimate an even larger effect of the destination log alumni network size on the relative odds of jointly moving to the destination and finding re-employment at a firm with another co-alumni (1.12%, p-value < 0.01). By contrast, we find a much smaller effect on the relative likelihood of moving to the destination and finding re-employment at a firm without any co-alumni present (0.56%, p-value < 0.01).

We also find that, in contrast to our out-mobility analysis, these large effects of destination network size on the location choice of movers are even more pronounced for younger job seekers. In Panel II of Figure 6, we re-estimate our gravity equation in Equation 10 separately for older (≥ 35) and younger (≤ 40) workers. Our dependent variable is now the number of o to d movers from school s within each age group. Conditional on moving, we find that younger workers are more likely to choose a destination city that experiences a 1% increase in its co-alumni network size, with a large estimated elasticity of odds (1.1%, p-value < 0.01), than older workers (estimated elasticity of 0.64%, p-value < 0.01). The lower propensity to stay in the origin post-displacement and the very large mobility response of younger job seekers to increases in destinations' alumni network sizes suggests that younger job seekers are quite willing to move to where their networks are.

Altogether, despite our focus on more broadly defined networks that primarily include individuals with whom job seekers in our sample have had no prior interaction, we find strong impacts of alumni network size on both out-mobility and directed migration. These findings strengthen a burgeoning literature on social networks and migration that has focused on more personalized networks (Büchel et al. 2020; Green 2024; Koenen and Johnston 2024).[45] In our unique setting in which the social networks we study are more directly related to job search, we additionally find even greater impacts of social networks on joint mobility and in-network re-employment. In light of job search's outsized importance in determining inter-metro migration, this finding suggests that college alumni networks play a significant role in influencing the geographic mobility of college-educated workers in the US.

We note, however, that other factors may still have a greater impact on geographic mobility. For instance, our estimated elasticities of the odds of migration with respect to the co-alumni network size in a destination are smaller than estimated elasticities of migration with respect to net-of-tax rate (Kleven et al. 2014) or tax rate differentials (Moretti and Wilson 2017).[46] This result is perhaps unsurprising, since earnings are a key component of indirect utility in many models of location choice, including ours to the extent that work utility nests earnings, and changes in tax rates directly and saliently change earnings. By comparison, changes in alumni network size impact earnings only by indirect means, through various job search-related mechanisms.

Our directed mobility results are robust to the same tests as for the out-mobility results detailed above, as well as additional tests. First, we consider a non-nested multinomial logit structure in which job seekers choose among all possible locations, including the origin, non-sequentially. We provide more details in Appendix D.2. In Table A.2, we re-estimate Equation 10 but for both movers and stayers, and obtain an estimated elasticity of location choice with respect to network size that is slightly larger than our estimate of β^{Stay} but smaller than our estimate of $\widetilde{\beta}^{Leave}$. This is sensible given that the multinomial logit structure delivers a singular β that governs both the out-mobility and directed migration margins.

From this framework, we also derive and estimate an alternative gravity equation based on Moretti and Wilson (2017). This specification, Equation 25 in Appendix D.2, is a log-odds gravity equation estimated via OLS. This approach unfortunately drops many observations from our sample due to zero within-school flows between many origins and destinations that are more effectively handled via PPML estimation. But since identification relies on destination-origin differences in alumni network size, we can directly include destination $\times$ school fixed effects to absorb any remaining concerns about within-school correlated pref-

[45] As a point of comparison, Koenen and Johnston estimate that one additional Facebook friend in a commuting zone increases the probability of locating there by 0.33 percentage points. In our setting, one additional co-alumni does not have the same impact on mobility, but any change in alumni network size beyond a small percentage increase would.

[46] Our elasticities with respect to local alumni network size are between a third to half as large as those in Kleven et al. (2014).

erences and city-school determinants of work utility in non-origin cities. We present OLS estimates in Table A.3. Reassuringly, even with destination × school fixed effects, our estimates of the elasticity (odds) of choosing a destination over staying in the origin, with respect to a change in the destination-origin alumni network size difference, are between our estimates of β^{Stay} and $\widetilde{\beta}^{Leave}$.

Next, we re-estimate Equation 10 using Bachelor's-degree-only alumni networks and present results in Table A.5. We find slightly smaller estimated effects to baseline, but still similar in magnitude, providing reassurance that our results are not driven by workers with post-Bachelor's education.

Next, we address the concern that workers may be especially attached to the metro they attended school in. As in the robustness checks in Section 5.1, we repeat our analysis using only workers who experience job loss outside their school's metro and present results in Table A.7. We find similar estimated elasticities as in our baseline specification. One might additionally worry that our results are driven by "return migration", or workers moving back to the metro they went to school in, where they tend to have large alumni networks. Only 6% of job seekers who are displaced outside their "home metro" actually make this choice. Nevertheless, in Table A.8 we exclude such individuals. Unsurprisingly, the resulting treatment effect is slightly smaller, but remains both large and statistically significant.

We address the possibility of location preferences varying across demographic groups by estimating expanded versions of our gravity equation that collapses counts of movers to the origin-destination-school-demographic group level (in comparison to origin-destination-school in our baseline analysis). We define demographic groups in the same manner as our parallel exercise for out-mobility in Section 5.1. Table A.10 reports estimates that are very similar to our baseline estimates.

We also estimate an expanded version of our gravity equation that includes firm-specific heterogeneity. We relate counts of movers collapsed to the origin-destination-school-firm level to destination alumni network size, and directly control for factors that vary across school-firm pairs and destination-firm pairs. Table A.12 reports our estimated elasticities from these models, which are very similar to our baseline estimates.

Likewise, we estimate an expanded version of our gravity equation that includes major-specific heterogeneity. We relate counts of movers collapsed to the origin-destination-school-major level to destination alumni network size, and directly control for factors that vary across school-major pairs and destination-major pairs. Our estimates, as reported in Table A.14, are very similar to our baseline estimated elasticities.

Finally, we consider an alternative measure of destination alumni network size that does not depend on job seekers' years of displacement. We calculate network size based on the yearly average across 2010-2019, rather than the average across years of displacement within an origin-school pair. Table A.16 shows virtually no effect on our estimated effects.

6 The Role of Peers and Same-Industry Networks

In this section, we analyze two mechanisms by which local co-alumni networks can influence geographic mobility. First, we consider the role of strong, weak, and potential weak ties. Specifically, we estimate the impact of both same-cohort and non-cohort co-alumni network size in a potential destination on location choice. Finally, we analyze to what extent a city's concentration of co-alumni in the same industry from which a job seeker was displaced affects that job seeker's geographic mobility.

6.1 *Same-Cohort Co-Alumni Networks and the Role of Direct Peers*

Our theoretical framework and primary analyses define a local co-alumni network as the entire set of alumni from a particular school in a given city. This broad definition nests strong ties — a job seeker's close personal network from school; weak ties — loose connections with other co-alumni that the job seeker knows personally; and potential ties — co-alumni that may show up on LinkedIn but are outside of the job seeker's personal network (Granovetter 1973). A job seeker's co-alumni network in a given city largely consists of potential ties from cohorts with whom they had no interaction during school. However, this does not necessarily mean that these potential connections from a job seeker's *alma mater* exert a stronger influence on geographic mobility than direct peers — strong, weak, or potential ties from the same or adjacent cohorts in the local co-alumni network. If the local co-alumni network's value in job search primarily comes from direct referrals and the transmission of job information from personal LinkedIn connections, or if job seekers strongly prefer to reside near friends and acquaintances from school, then the network's overall impact on geographic mobility instead stems from the job seeker's smaller network of peers from the same or adjacent cohorts.

To test this possibility, we quantify the impact of both same-cohort and non-cohort local co-alumni network size on the location choice of job seekers. We define the same-cohort alumni network size as the log number of co-alumni from same and neighboring cohorts of the same highest degree.[47] Consequently, the non-cohort alumni network size is the log number of co-alumni who either did not complete the same degree as the job seeker or do not belong to the same or a neighboring cohort.

To test the relative strength of the two networks, we decompose the impact of total

[47]For Bachelor's degrees, the set of neighboring cohorts for some graduating year t is $[t-3, t+3]$. For Master's degrees and MBA degrees, the set of neighboring cohorts is $[t-1, t+1]$. For doctorate degrees, the set of neighboring cohorts is $[t-4, t+4]$.

network size into separate effects of same-cohort and non-cohort alumni network size, in both the city of origin and alternative destinations, on a job seeker's indirect utility. Thus we estimate four parameters of interest: $\beta^{Stay,c}$ and $\beta^{Stay,-c}$ rather than a singular β^{Stay}; as well as $\widetilde{\beta}^{Leave,c}$ and $\widetilde{\beta}^{Leave,-c}$ rather than a singular $\widetilde{\beta}^{Leave}$. Here, c refers to same-cohort and $-c$ refers to non-cohort. We estimate $\beta^{Stay,c}$ and $\beta^{Stay,-c}$ using the appropriately modified form of our binary logit in Equation 9:

$$\log\left(\frac{Pr(stay_i)}{1-Pr(stay_i)}\right) = \alpha + \beta^{Stay,c}\log(\sigma_{ose_i,c}) + \beta^{Stay,-c}\log(\sigma_{ose_i,-c}) \\ + X_i'\eta + \delta_{e_i} + \phi_{oK(s)} - \lambda\widehat{IV}_{osc} + \epsilon_{iosc} \tag{11}$$

Here, $\log(\sigma_{ose_i,c})$ and $\log(\sigma_{ose_i,-c})$ are same-cohort and non-cohort network sizes, respectively. The inclusive value $\widehat{IV}_{osc}$ is estimated from a modified version of Equation 10, using origin $\times$ school $\times$ cohort fixed effects in lieu of origin $\times$ school fixed effects and using both same-cohort and non-cohort log network size in lieu of total network size in a destination d. This same gravity equation yields consistent estimates of $\widetilde{\beta}^{Leave,c}$ and $\widetilde{\beta}^{Leave,-c}$, as follows:

$$P_{odsc} = \exp(\widetilde{\beta}^{Leave,c}\log(\sigma_{ds,c}) + \widetilde{\beta}^{Leave,-c}\log(\sigma_{ds,-c}) + \phi_{osc} + \phi_{od} + \phi_{dK(s)})\varepsilon_{odsc} \tag{12}$$

Here, our dependent variable is the number of job seekers from school s and graduating in cohort c, defined as the graduation year and degree of highest completion, e.g. Bachelor's, MBA, etc., who are displaced in city o and move to city d one year post-displacement. Our primary explanatory variables are $\log(\sigma_{ds,c})$ and $\log(\sigma_{ds,-c})$, the log number of same-cohort and non-cohort alumni, respectively, in d.

We display our estimates of $\beta^{Stay,c}$ and $\beta^{Stay,-c}$ in Panel I of Figure 7, and our estimates of $\widetilde{\beta}^{Leave,c}$ and $\widetilde{\beta}^{Leave,-c}$ in Panel II. We find that for both the stay vs. leave decision and the choice over all alternative destinations conditional on moving, the estimated impact of same-cohort network size ($\beta^{Stay,c}$ and $\widetilde{\beta}^{Leave,c}$) on our two mobility margins is greater than that of non-cohort network size. In the case of directed migration, our estimate of $\widetilde{\beta}^{Leave,c}$ (0.69, p-value < 0.01) is over twice as large as our estimate of $\widetilde{\beta}^{Leave,-c}$ (0.27, p-value $<$ 0.01).

Thus our results suggest particularly strong roles for same-cohort alumni in impacting the geographic mobility of college-educated job seekers. This impact is notable given that same-cohort networks are much smaller (non-cohort networks in the city of displacement are over 6 times as large, on average).[48] Our estimates with respect to both same-cohort

[48]The mean same-cohort network size across job seekers' cities of displacement is about 2,400 co-alumni, whereas the mean non-cohort network size is over 14,000 co-alumni.

and non-cohort network size imply that one additional co-alumni with whom a job seeker overlapped during school exerts the same impact on mobility as several additional co-alumni from non-adjacent cohorts.

Our significantly higher estimated impacts of same-cohort alumni network size also suggest that our estimated impacts of local alumni network size on both out-mobility and directed migration capture a true network effect. Idiosyncratic match effects between alumni from a specific school and firms in a specific city are not tied to direct or potential connections between network members. Consequently, such effects are common to different cohorts from the same school. By contrast, co-alumni who graduated around the same time as a job seeker are the most likely network members to interact with the job seeker during the job search process. Our finding of even higher effects from these members speaks to a phenomenon that extends beyond match effects that are far more cohort-invariant.

6.2 *Co-Alumni Networks and Industry-Specific Human Capital*

In this section, we consider a more granular definition of a local co-alumni network, specifically the number of co-alumni in a local labor market who work in the same industry from which a job seeker is displaced.[49] We ask whether a higher concentration of co-alumni who work in a job seeker's city and industry of displacement increases the probability that the job seeker stays in that city. We acknowledge that workers are mobile across industries, but our paper's focus is on geographic mobility specifically, and we do not model a job seeker's joint location and industry choice.

We motivate our focus on same-industry co-alumni networks by first noting that our sample of job seekers has, on average, more than a decade of labor market experience and thus consists of many individuals who have accrued significant industry-specific human capital (Neal 1995; Parent 2000). For such job seekers, displacement can be very costly if they cannot find new employment in the same industry. To capture the relationship between industry-specific human capital and earnings, we now assume that the number of job draws a job seeker can have in a particular city is proportional to the number of local same-industry alumni rather than all alumni. Thus work utility y_{ds} is log-linear in a city's number of same-industry alumni. We discuss this modification in greater detail in Appendix D.3.

We continue to assume that the amenity value of having more co-alumni in a particular city is constant across a school's alumni and not tied to a job seeker's industry of displacement. To the extent that job seekers differentially value same-industry versus different-industry co-alumni for non-job reasons, our estimates of local industry co-alumni network size on mobility could partially capture this mechanism in addition to job search channels.

[49] As in previous sections, our industry definition is a 2-digit NAICS code.

We begin by testing whether an increase in the number of same-industry co-alumni in a job seeker's city of displacement o increases their likelihood of remaining in the same city. We estimate a modified version of Equation 9:

$$\log(\frac{Pr(stay_i)}{1 - Pr(stay_i)}) = \alpha + \beta^{Stay} \log(\sigma_{osje_i}) + X_i'\eta + \delta_{e_i} + \phi_{os} - \lambda\widehat{IV}_{osj} + \epsilon_{iosj} \tag{13}$$

Our primary explanatory variable is now $\log(\sigma_{ojse_i})$, the log number of alumni in metro o and industry j in the year of displacement who went to worker i's *alma mater* s. We can now identify β^{Stay}, without imposing any identifying assumptions about city-school work utility A_{ms} or correlated preferences Z_{ms} for any city m, by including destination $\times$ school fixed effects in the estimation of the inclusive value $\widehat{IV}_{osj}$ and origin $\times$ school fixed effects ϕ_{os}.[50] Crucially, by including ϕ_{os} (and destination $\times$ school fixed effects in the estimation of the inclusive value), we fully absorb lingering threats to identification at the city-school level. We also absorb the impact of total network size in the city of origin.

Our second-step estimate of β^{Stay} is 0.456 (p-value < 0.01). In Figure 8, we show that this estimate is larger than our baseline estimate of the impact of total log alumni network size on out-mobility from Equation 9. We note that the two estimates are not perfectly comparable since our estimated effect of same-industry origin network size comes from a model that already absorbs the impact of total network size. Nevertheless, the large relative magnitude of our estimated coefficient on same-industry network size suggests that the presence of co-alumni who work in the industry from which a job seeker was most recently separated and had accrued meaningful industry-specific human capital influences out-mobility in a way that extends beyond the mere presence of all co-alumni.

Next, we show that increasing the number of same-industry co-alumni in a potential destination city increases the odds that a job seeker chooses to live and work in that city over another, conditional on moving. We incorporate even more industry-specific heterogeneity into our model by allowing for additional city $\times$ industry and school $\times$ industry work utility components.[51]. This inclusion additionally controls for factors such as UC Berkeley graduates potentially having strong productivity matches with firms in the Tech sector, or workers in the New York City Finance sector being more productive. We describe these additional modifications in Appendix D.3, and accordingly estimate the following extension of our

[50] We estimate $\widehat{IV}_{osj}$ using a modified version of Equation 10 at the origin $\times$ school $\times$ industry (of displacement) $\times$ destination level. We replace origin $\times$ school fixed effects with origin $\times$ school $\times$ industry fixed effects, and include same-industry network size in destination d instead of total network size. We replace destination $\times$ strata fixed effects with destination $\times$ school fixed effects, and estimate parameters via PPML.

[51] Recall in our baseline model, work utility is defined at the city-school level as y_{ds}

primary gravity equation used for our directed mobility analysis:

$$P_{odsj} = \exp(\widetilde{\beta}^{Leave} \log(\sigma_{dsj}) + \phi_{osj} + \phi_{od} + \phi_{ds} + \phi_{dj})\varepsilon_{odsj} \tag{14}$$

We estimate Equation 14 on data collapsed at the origin $\times$ destination $\times$ school $\times$ industry level, where P_{odsj} is the number of job seekers who went to school s and were displaced in industry j who move from o to d. We include origin $\times$ school $\times$ industry fixed effects ϕ_{osj} to absorb school $\times$ industry work utility factors and the combined attractiveness of all alternative destinations (see denominator in Equation 8b). We also include origin $\times$ destination fixed effects ϕ_{od} to absorb moving costs. Our inclusion of destination $\times$ school fixed effects ϕ_{ds} absorbs citywide co-alumni network size, correlated preferences and city-school work utility factors without requiring additional identifying assumptions. Finally, we include ϕ_{dj}, which are destination $\times$ industry fixed effects that control for location $\times$ industry-specific factors that impact work utility in each location.

We present our estimates in Table 9. In our most preferred specification in Column 3 that coincides exactly with Equation 14, our estimated elasticity of the odds of choosing a destination city, relative to another, with respect to the same-industry co-alumni network size in that destination, is 0.79% (p-value < 0.01). This estimate is similar to our estimated elasticity of the odds of choosing a destination city with respect to the total alumni network size, irrespective of industry, in that city. Since our inclusion of destination $\times$ school fixed effects already controls for the impact of total network size on location choice, our large estimate of the effect of local same-industry co-alumni network size on destination choice suggests that, as was the case for the stay vs. leave margin, same-industry co-alumni networks play a significant role in influencing the directed mobility of job seekers.

7 Conclusion

We show that local college alumni networks have a significant impact on the geographic mobility of exogenously displaced college-educated job seekers. Job seekers are both more likely to stay in the same local labor market post-displacement if they are locally surrounded by a higher concentration of co-alumni, and more likely to move to other local labor markets that have more co-alumni working there. The overall effect of local college alumni network size on mobility comes from both a network's value in job search and its direct value as a consumption amenity, with our evidence suggesting that the job search channel plays a strong role. College alumni networks in alternative destinations have a particularly strong impact on the directed migration of younger job seekers who are less likely to have built other social networks post-graduation. Finally, within a local labor market's stock of all graduates from a particular institution, those who were in a job seeker's same or neighboring cohorts as well as those employed in the same industry from which a job seeker was displaced have a particularly strong impact on their location choice.

Our study advances understanding of internal migration in the US, and potentially other large developed countries, by emphasizing a key determinant of the inter-metro mobility of the most mobile subpopulation — college-educated workers. If internal migration improves individual economic outcomes, then college alumni networks provide an indirect pathway for college-educated job seekers to potentially increase earnings and find better job matches, both locally and far away. In Figure 9 panel A, we show that for job seekers who move, the change in their alumni network size (new destination minus origin) is positively correlated with the change in citywide place effects on earnings from origin to destination.[52] In panel B of the same figure, when we regress this change in earnings premia (either an indicator for positive change or the actual magnitude) on the change in network size, conditioning on origin $\times$ strata fixed effects, we find a strong, positive relationship between moving to a metro with more co-alumni and moving to a metro with larger place effects. While this relationship is largely descriptive in nature, it suggests that networks drive not only mobility in itself but also mobility to areas of higher economic opportunity. Quantifying these gains with more precise earnings data would be insightful in future research.

We also underscore potential micro-foundations of agglomeration economies and economic spillovers in local labor markets. A strong presence of alumni from a particular school in a given city attracts more job seekers from the same school, and those job seekers overwhelmingly end up at the same firms where co-alumni already work. To the extent that this coincidence of connected college-educated workers at the same local firms exerts a meaningful influence on knowledge spillovers, labor market pooling and matching externalities, college alumni networks directly contribute to the existence of agglomeration economies. Furthermore, in the presence of human capital externalities and local multipliers that predict wage increases for workers without a college degree in response to an increase in a city's stock of college-educated workers, these networks can indirectly improve the economic outcomes of non college-educated workers.

These economic implications highlight many important considerations for policymakers. Local governments often incentivize firms to relocate nearby. This relocation could simply reallocate college-educated workers who were already in the local area. Yet if these firms have a large presence of co-alumni from any particular school(s), then network-induced directed mobility could drive a possibly larger influx of college-educated workers from those

[52] We use estimates of commuting zone earnings premia from Card, Rothstein, and Yi (2025), and map commuting zones to our metro areas using county-level population weights.

schools and the ensuing economic impacts of this migration. Other local policies such as Idaho's House Bill 718 might provide subsidies for students conditional on those students remaining in-state for some time post-graduation (Idaho House Bill 718, 2022), which could encourage other co-alumni to also return to the local area in the future. From a broader welfare perspective, however, tradeoffs between aggregate economic efficiency and spatial inequality must be taken into consideration. While a local government may prioritize policies that capitalize on alumni networks' influence on geographic mobility to encourage more in-migration of college-educated workers, this inflow may come at the expense of a more productive local labor market that in turn loses these workers. Evaluating these tradeoffs is of great policy importance, and a promising line of future research.

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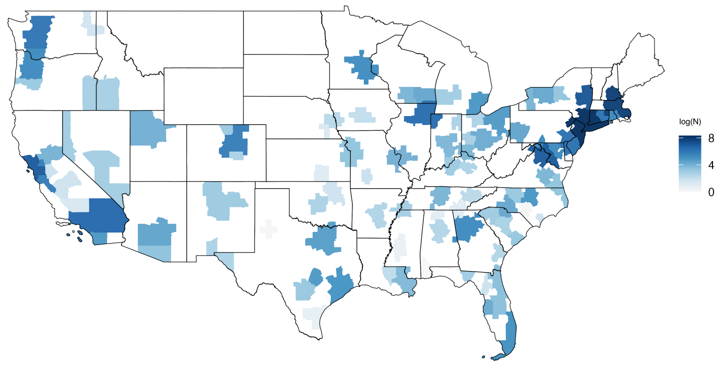
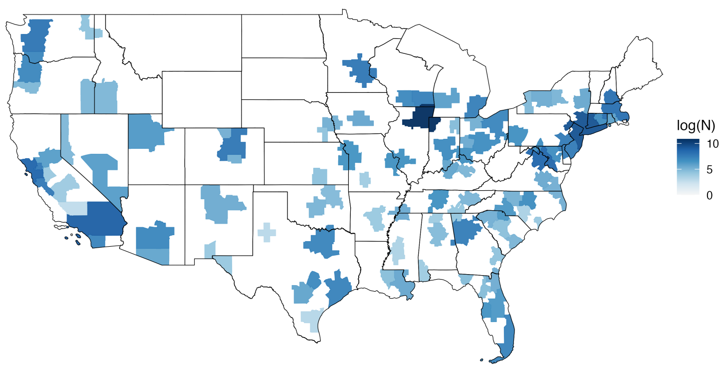
Figures and Tables

Figure 1: College Alumni Network Size Across Local Labor Markets, by School



(a) Williams College



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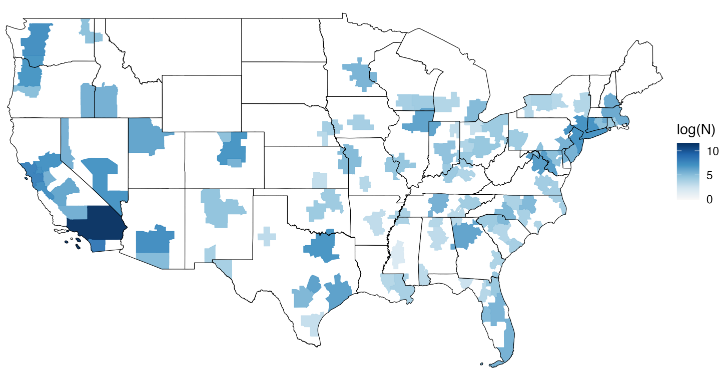
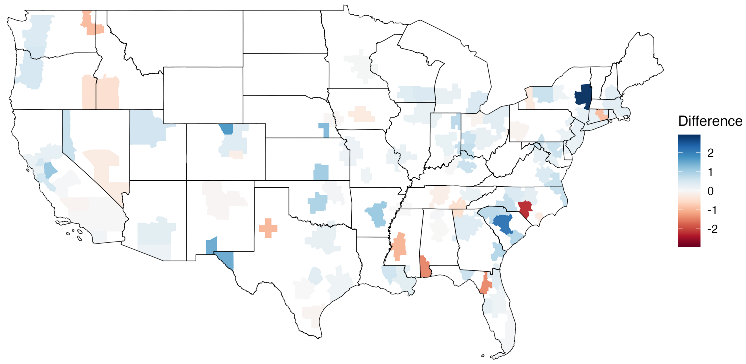


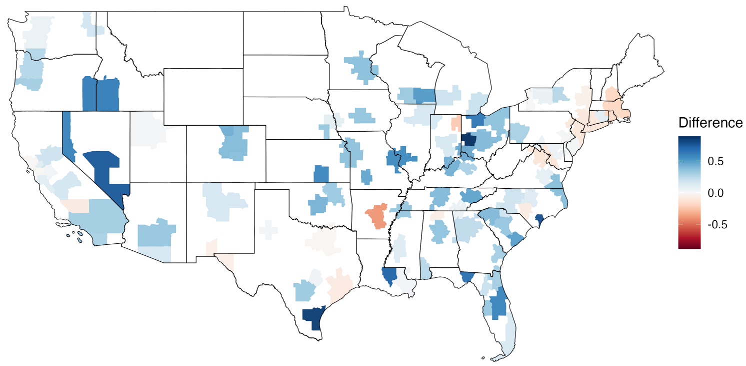
(c) CSU Fullerton

Notes: The heat maps show the 2010-2019 yearly average log number of alumni (across all degree types) from the schools in panels a-c that are working in each metro area. Counts of alumni are obtained from self-reported educational histories on LinkedIn profiles observed in the Revelio Labs data. Our three panels correspond to different types of schools: a) a small, highly selective liberal arts college; b) a mid-sized, highly selective private university; and c) a large, non-highly selective public university.

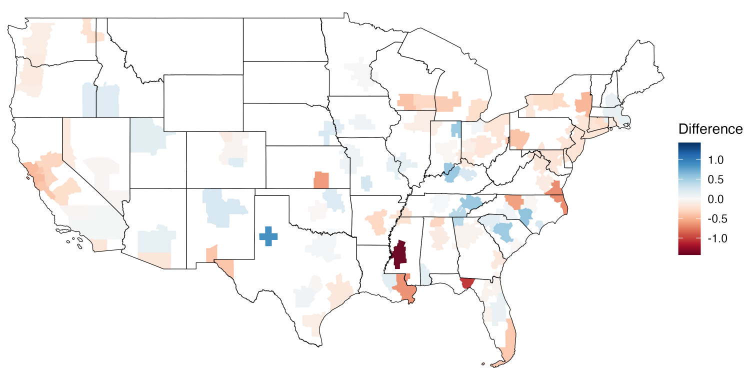
Figure 2: Differences in Alumni Network Size Across Local Labor Markets, by School Pair



(a) Amherst College (red) and Williams College (blue)



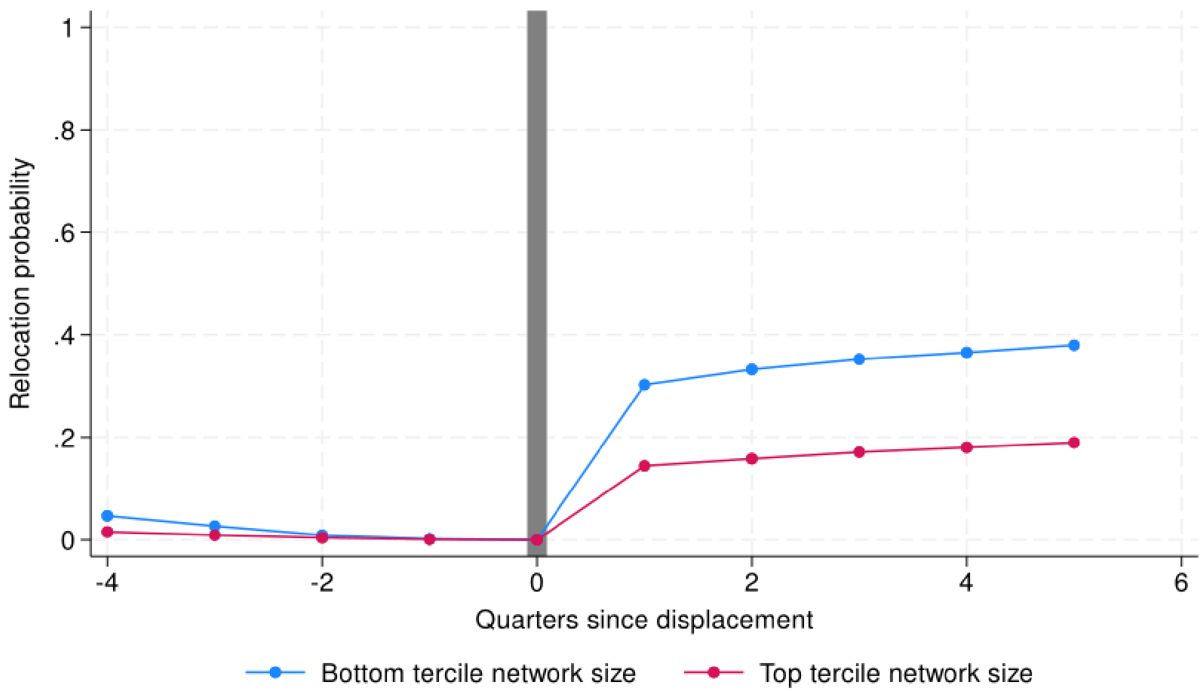
(b) University of Chicago (red) and Northwestern University (blue)



(c) CSU Long Beach (red) and CSU Fullerton (blue)

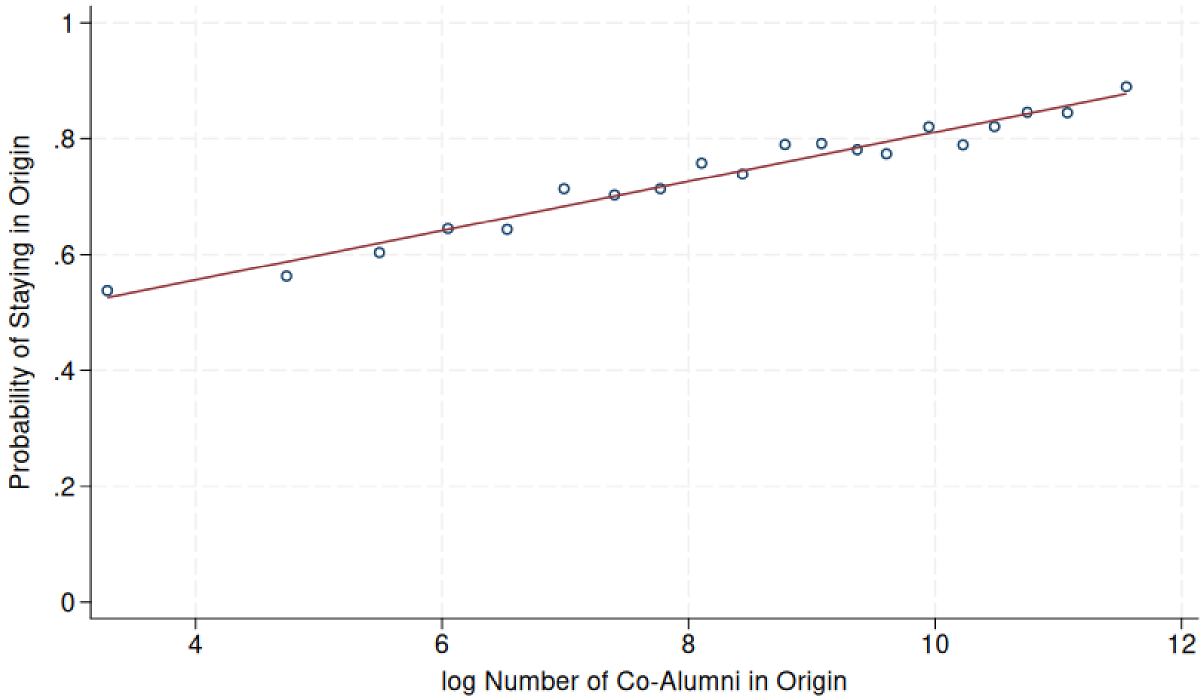
Notes: The heat maps show the difference in 2010-2019 yearly average log number of alumni (across all degree types) that are working in each metro area between pairs of highly similar, geographically proximate schools in panels a-c. Counts of alumni are obtained from self-reported educational histories on LinkedIn profiles observed in the Revelio Labs data. Our three panels correspond to pairs of 3 different types of schools: a) highly selective small liberal arts colleges in Massachusetts; b) elite mid-sized universities in the Chicago metro area; and c) large universities in the Los Angeles metro area that belong to the California State University System.

Figure 3: Probability of Relocation, Large vs. Small Local Alumni Network



Notes: This plot compares the relocation probabilities of workers displaced in cities with large vs. small alumni networks. We plot the share of workers in our sample who have ever worked in a different metro from their metro in the quarter of displacement $\tau = 0$, for each quarter τ after displacement. For quarters prior to displacement, we plot the share of workers who are in a different metro from their metro at $\tau = 0$. We split the sample by top and bottom population-weighted terciles of local college alumni network size. In other words, for a given school, we define the top tercile as the cities with the largest number of alumni from that school who account for the first third of the entire alumni population. Similarly, the bottom tercile is the set of cities with the smallest number of alumni from the school who account for the final third of the school's alumni population.

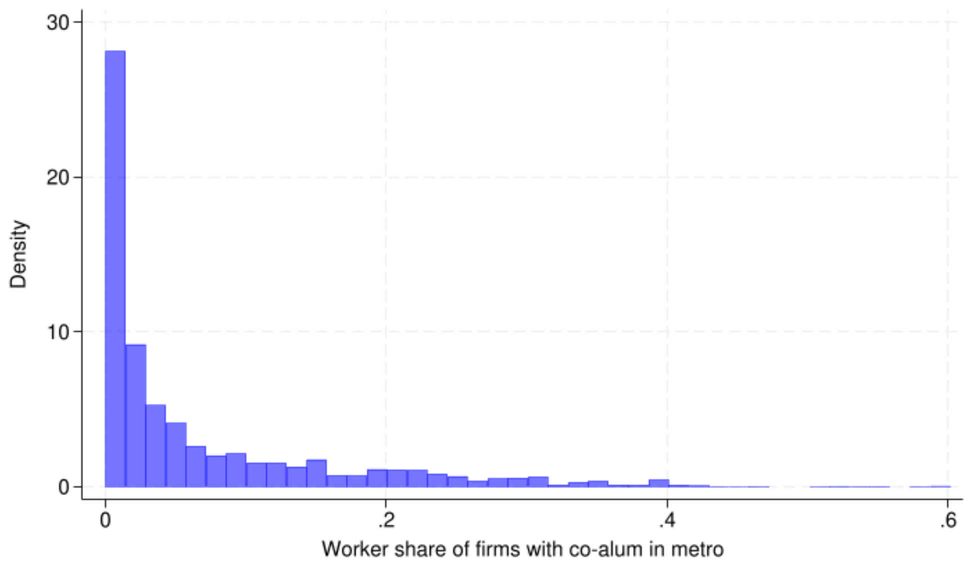
Figure 4: Relationship Between Probability of Staying in City of Displacement and log Alumni Network Size



Notes: This plot shows the relationship between alumni network size in the city of displacement and the probability of staying post-displacement. We partition the log yearly average (2010-2019) number of alumni in each job seeker's city of displacement into bins. For each bin, we plot the average (across job seekers) probability of staying in the same city 1 year post-displacement.

Figure 5: Concentration of and Re-Employment at Local In-Network Firms

Panel A: Share of Local Firms with Co-Alumni Across Job Seekers



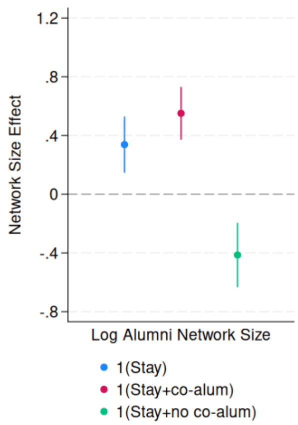
Panel B: Share of Workers Re-Employed at In-Network Firms

	Share of workers w/ co-alum at firm	Share of firms in metro w/ co-alum (mean)	Share of firms (10+ employees) in metro w/ co-alum (mean)
All	0.66	0.07	0.22
By experience			
0 to 5-yr post-grad	0.69	0.07	0.23
6 to 10-yr post-grad	0.68	0.07	0.22
11 to 20-yr post-grad	0.66	0.07	0.22
20-yr+ post-grad	0.61	0.06	0.20
By school type			
Public school grad	0.70	0.09	0.26
Private school grad	0.59	0.03	0.14
By school size			
Less than 5,000 students	0.60	0.03	0.11
5,000-20,000 students	0.66	0.05	0.17
20,000+ students	0.73	0.10	0.30

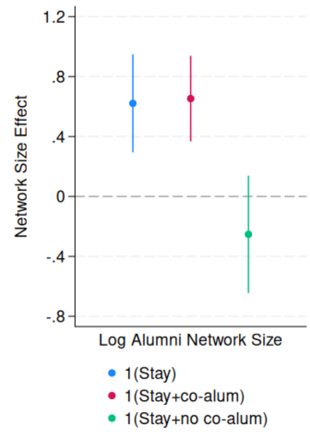
Notes: In Panel A, we plot, across all displaced job seekers in our sample, a histogram of the share of firms in their respective cities 1 year post-displacement that have at least one co-alumni (in-network firm). In Panel B, we report the mean of this share in the middle column. In the right-most column, we report the mean share of in-network firms among local firms with 10+ employees. In the left-most column, we report the share of workers who are re-employed at an in-network firm 1 year post-displacement. We report these statistics for various subpopulations of our sample. In the top row, we include all displaced job seekers who are re-employed 1 year post-displacement. The next block splits the sample into groups of workers who have different amounts of labor market experience. In the third block, we split the sample into workers who matriculated from public vs. private schools. In the final block, we split job seekers by the size of their *alma maters*.

Figure 6: Effect of Local Alumni Network Size on Mobility, by Age

I) Effect of Origin Alumni Network Size on Probability of Staying, by Age

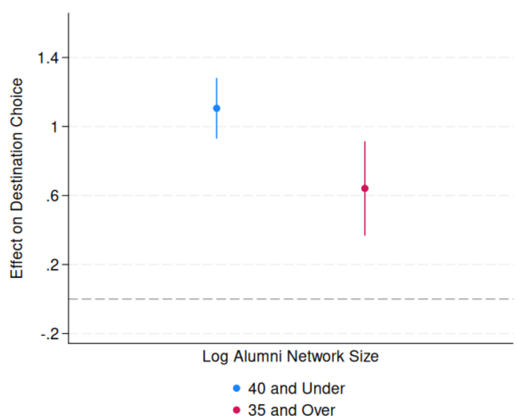


(a) 40 and Under



(b) 35 and Over

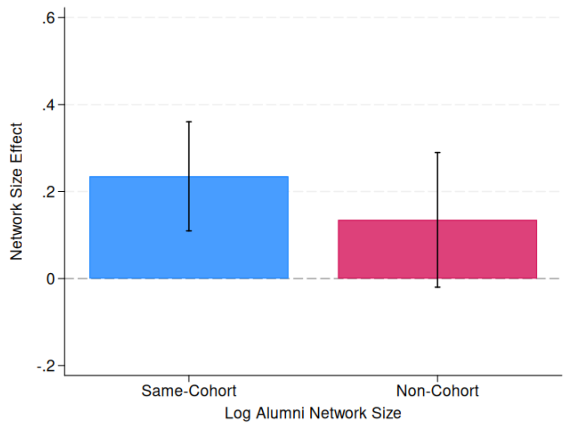
II) Effect of Destination Alumni Network Size on Directed Migration, by Age



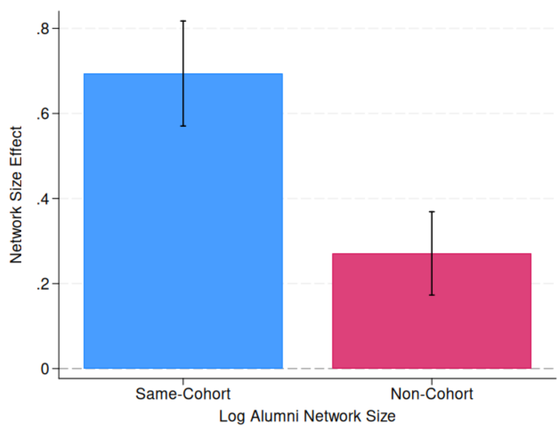
Notes: We plot estimates of the impact of network size in the city of displacement (origin)/destination on out-mobility/directed migration, separately by age group. Panel I estimates Equation 9 separately for workers 40 years old and younger (a) and 35 and over (b). Baseline estimates for all workers are in Table 5. We estimate logits with three dependent variables: indicators for whether a displaced worker stays in the origin 1 year post-displacement (1(Stay)); jointly stays and has a co-alum at their new firm (1(Stay+co-alum)); and jointly stays but without any co-alums at their new firm (1(Stay+no co-alum)). All models include the inclusive value of leaving (estimated from Equation 10); individual controls: gender, race, age and age-squared; year of displacement fixed effects; and origin × school strata fixed effects, with strata defined in Data Appendix B.3. Standard errors are bootstrapped, with 400 reps resampling clusters at the origin × school level. Panel II plots estimates from Equation 10 via Poisson pseudo-maximum likelihood (PPML), separately by age group. Dependent variable is the number of displaced alumni from school s in city o in each age group who move to city d 1 year post-displacement. We include origin × destination fixed effects, origin × school fixed effects, and destination × school strata fixed effects. Standard errors are clustered three-ways by origin × destination, origin × school, and destination × school. 95% confidence intervals are drawn for each estimate.

Figure 7: Effect of Same-Cohort and Non-Cohort Co-Alumni Network Size on Out-mobility and Directed Migration

I) Out-mobility

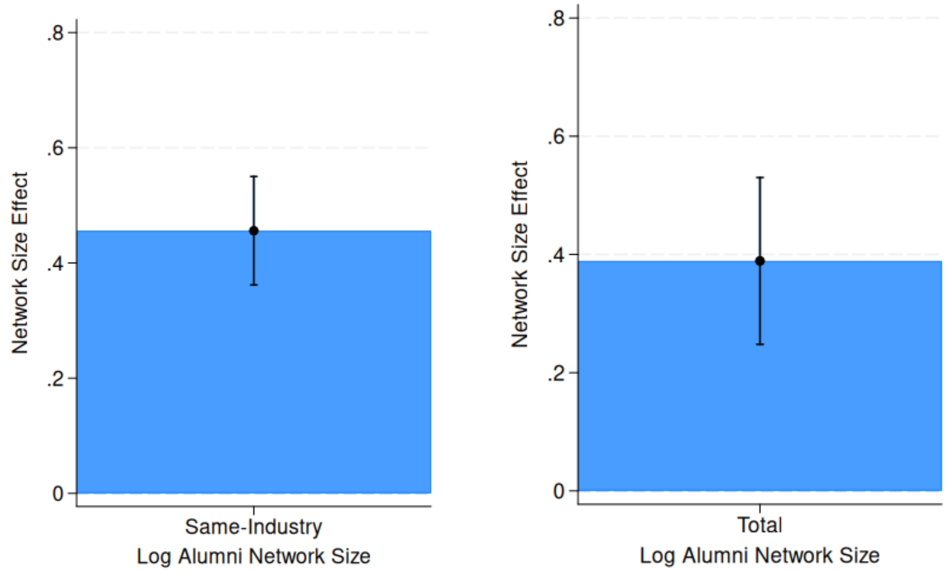


II) Directed Migration



Notes: We plot estimates of the impact of same-cohort and non-cohort network size on out-mobility and directed migration. Panel I presents estimates from Equation 11 for out-mobility — a logit with the outcome as an indicator for whether a displaced worker stays in the same metro (origin) 1 year post-displacement. We plot the estimated coefficients on the log number of co-alumni in the origin who are and are not in the job seeker's graduating or neighboring cohort, respectively. We define cohort as the graduation year $\times$ degree of highest completion. We include the inclusive value of leaving; individual controls: gender, race, age and age-squared; year of displacement fixed effects; and origin $\times$ school strata fixed effects. School strata are defined as in Data Appendix B.3. Standard errors are bootstrapped, with 400 reps resampling clusters at the origin $\times$ school $\times$ cohort level. Panel II plots estimates of same (and neighboring)-cohort network size and non-cohort network size's impacts on destination choice, conditional on moving, from Equation 12 estimated via PPML. Dependent variable is the number of displaced alumni from school s and cohort c in city o who move to city d 1 year post-displacement. We include origin $\times$ destination fixed effects, origin $\times$ school $\times$ cohort fixed effects, and destination $\times$ school strata fixed effects. Standard errors are clustered three-ways by origin $\times$ destination, origin $\times$ school, and destination $\times$ school. 95% confidence intervals are drawn for each estimate.

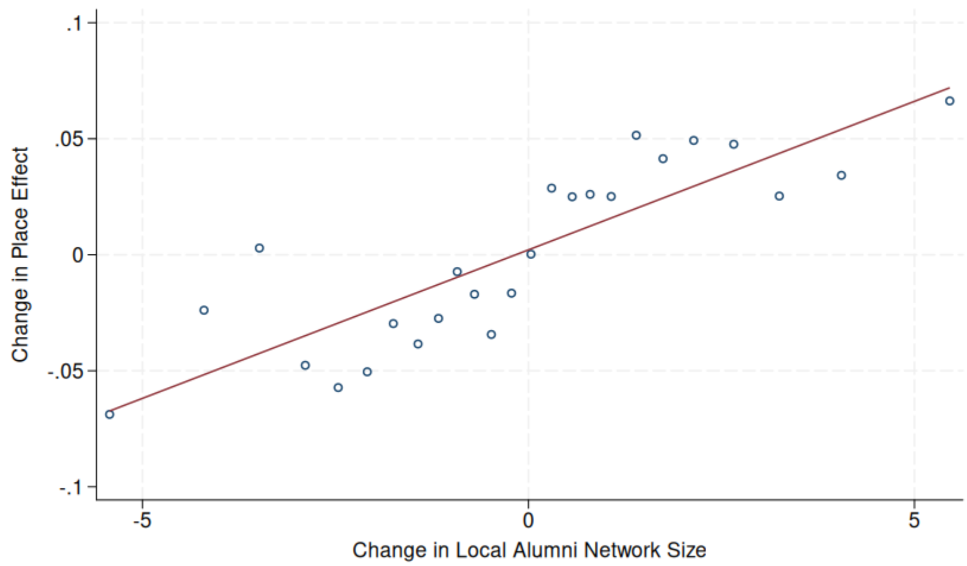
Figure 8: Effect of Same-Industry Co-Alumni Network Size on Out-mobility



Notes: We plot the coefficient on same-industry log alumni network size in our out-mobility logit from Equation 13 (left), alongside the coefficient on total log alumni network size in our separate baseline out-mobility logit from Equation 9 (right). Outcome is an indicator for whether a displaced worker stays in the same metro 1 year post-displacement. Our estimate of the same-industry network size effect comes from a model that already includes origin × school fixed effects, and whose estimated inclusive value comes from a gravity equation, Equation 10, that directly includes destination × school fixed effects and same-industry network size in the destination. The origin × school fixed effect thus absorbs the impact of total network size in the origin on out-mobility. Also included are the same additional controls and fixed effects in column 3 of Table 2. Standard errors are bootstrapped, with 400 reps resampling clusters at the city × school × industry level (city × school level for total network size analysis). On the right side, we plot our baseline estimate of origin total network size's impact on the probability of staying, from column 3 of Table 2. See table notes for Table 2 for more details. We examine the impact of same-industry network size on directed migration in Table 9.

Figure 9: Relationship Between Changes in Local Alumni Network Size and Changes in Citywide Earnings Premia

Panel A: Raw Correlation Across Movers



Panel B: Correlation Within Origin and Strata

	Outcome	
	1(Δ Place Effect > 0)	Δ Place Effect
	(1)	(2)
1-Year Change in log Number of Co-Alumni	0.016**	0.010***
	(0.007)	(0.002)
Observations	2,067	2,067
Origin x school strata FE	X	X

Notes: We show descriptively that job seekers, conditional on moving, relocate to cities with both higher network sizes and higher earnings premia. In Panel A, we partition the difference in log alumni network size between a job seeker's city of displacement (origin) and their city 1 year post-displacement (destination) into bins, for movers only. For each bin, we plot the average destination-origin difference in citywide earnings premia from Card, Rothstein and Yi (2025). The earnings premia calculated in Card, Rothstein and Yi (2025) are at the commuting zone level, which we map to our metro areas based on county population weights. In Panel B, we regress, for movers only, an indicator for a positive destination-origin difference in earnings premia (column 1) and the actual difference (column 2) on the difference in log alumni network size between destination and origin. We include origin × school strata fixed effects. School strata are defined as in Data Appendix B.3. Standard errors are clustered at the origin × school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 1: Summary Statistics for Job Seekers at Time of Displacement

	All		Top Tercile		Bottom Tercile	
	mean	sd	mean	sd	mean	sd
Number of Co-Alumni in Metro	17371.47	27393.98	33874.02	33268.70	3848.16	12580.25
Age	35.56	9.25	34.64	8.84	36.76	9.68
Female	0.35	0.48	0.37	0.48	0.34	0.48
White	0.81	0.39	0.80	0.40	0.81	0.39
Asian	0.07	0.25	0.07	0.26	0.06	0.24
Black	0.07	0.25	0.07	0.25	0.07	0.25
Hispanic	0.05	0.22	0.06	0.23	0.06	0.23
Other	0.00	0.06	0.00	0.07	0.00	0.05
Predicted Salary of Laid-Off Position	83585.23	41288.72	82982.27	41776.13	80908.28	38427.85
Observations	20459		8807		6904	

Notes: We present summary statistics for our sample of displaced job seekers at the time of displacement. We split the sample by top and bottom population-weighted terciles of local college alumni network size, within school and across metros. In other words, for a given school, we define the top tercile as the cities with the largest number of alumni from that school who account for the first third of the entire alumni population. Similarly, the bottom tercile is the set of cities with the smallest number of alumni from the school who account for the final third of the school's alumni population. Age is imputed based on year of entry to the worker's Bachelor's degree program. Female and ethnicity is predicted from a user's name on their LinkedIn profile. Predicted salary comes from a model, developed by Revelio Labs, taking firm, location, occupation, etc. as inputs.

Table 2: Effect of Alumni Network Size in City of Displacement on Probability of Staying

	Outcome: 1(Stay metro 1-year post-displacement)		
	(1)	(2)	(3)
log Number of Co-Alumni	0.325***	0.426***	0.389***
	(0.012)	(0.061)	(0.072)
Inclusive Value	-0.487***	-0.386***	-0.367***
	(0.045)	(0.089)	(0.110)
Average Marginal Effect of	0.054***	0.067***	0.060***
log Number of Co-Alumni	(0.002)	(0.009)	(0.011)
Observations	17,435	12,943	10,743
Individual controls	X	X	X
Institutional controls	X	X	
Layoff year FE	X	X	X
Origin FE	X		
Origin x school metro FE		X	
Origin x school strata FE			X

Notes: Estimates from second-step logit in Equation 9. Dependent variable is an indicator for whether a displaced worker stays in the same metro 1 year post-displacement. Estimation proceeds in two steps. In a first step, we estimate, via Poisson pseudo-maximum likelihood (PPML), the parameters in our choice probability model (Equation 8b) using our gravity equation for destination choice (conditional on moving) in Equation 10. We use these estimates to construct the inclusive value. In our second step, we estimate logits at the worker level. All models include individual controls: gender, race, age and age-squared. Columns 1 and 2 include institutional controls, namely school size. We include fixed effects for the calendar year of displacement in all columns. In column 1 we include origin fixed effects, which are replaced in column 2 by origin × school metro fixed effects, and finally replaced by origin × school strata fixed effects in column 3. School strata are defined as in Data Appendix B.3. Standard errors are bootstrapped, based on 400 reps and cluster resampling at the city × school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 3: Effect of Alumni Network Size in City of Displacement on Probability of Staying — Logit and Saturated Linear Probability Models

	Outcome: 1(Stay metro 1-year post-displacement)			
	Logit	LPM		
	(1)	(2)	(3)	(4)
log Number of Co-Alumni	0.389***	0.061***	0.070***	0.050***
	(0.072)	(0.012)	(0.023)	(0.014)
Inclusive Value	-0.367***	-0.060***	-0.084	-0.042**
	(0.110)	(0.018)	(0.053)	(0.020)
Average Marginal Effect of	0.060***	0.061***	0.070***	0.050***
log Number of Co-Alumni	(0.011)	(0.012)	(0.023)	(0.014)
Observations	10,743	11,135	11,012	9,221
Individual controls	X	X	X	X
Layoff year FE	X	X	X	X
School FE			X	
Origin x school strata FE	X	X	X	
Origin x school strata x industry FE				X

Notes: Estimates from second-step logit and linear probability model (LPM) approximations in Equation 9. Dependent variable is an indicator for whether a displaced worker stays in the same metro (origin) 1 year post-displacement. Estimation proceeds in two steps. First, we estimate, via Poisson pseudo-maximum likelihood (PPML), the parameters in our choice probability model (Equation 8b) using our gravity equation for destination choice (conditional on moving) in Equation 10. We use these estimates to construct the inclusive value of leaving. In our second step, we estimate worker-level logits and LPMs. All models include individual controls: gender, race, age and age-squared; and year of displacement fixed effects. Column 1 reports our baseline logit estimate, with column 2 as the LPM equivalent. School strata are defined as in Data Appendix B.3. In column 3, we add school fixed effects to the LPM in column 2. In column 4, we replace origin × strata fixed effects and school fixed effects with fully interacted origin × strata × industry of displacement fixed effects. Standard errors are bootstrapped, with 400 reps and cluster resampling at the city × school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 4: Effect of Alumni Network Size in City of Displacement on Probability of Staying — Control Function Approach with Instrumental Variable

	Outcome: 1(Stay metro 1-year post-displacement)	
	CF+IV	Baseline
	(1)	(2)
log Number of Co-Alumni	0.478**	0.389***
	(0.206)	(0.072)
Inclusive Value	-0.327**	-0.367***
	(0.138)	(0.110)
Observations	10,068	10,743
First Stage	1.422***	
	(0.076)	
F-statistic	349.3	
Individual controls	X	X
Layoff year FE	X	X
Origin x school strata FE	X	X

Notes: Column 1 reports our two-stage residual inclusion (2SRI) estimate of β^{Stay}, the effect of alumni network size in the city of displacement (origin) on the probability of staying, using a control function approach with an instrumental variable, alongside our baseline estimate of β^{Stay} from Table 2 column 3. Our instrument is $W_{os} = \frac{Share_{s,1972}}{1+dist_{os}}$, where $Share_{s,1972}$ is a school's share of in-state students in 1972 and $dist_{os}$ is the great circle distance between origin and school in miles. In a first stage, origin log network size in a given year is regressed on W_{os}, $dist_{os}$, the estimated inclusive value of leaving, origin $\times$ school means of individual controls (gender, race, age and age-squared), year of displacement fixed effects, and origin $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3. The inclusive value comes from 2SRI estimates, via Poisson pseudo-maximum likelihood (PPML), of parameters in our choice probability model plus a first stage residual (Equation 21). Our first stage is estimated at the origin $\times$ school $\times$ year of displacement level, weighted by number of individuals in each cell, with 10,424 observations. First stage standard errors are clustered at the origin $\times$ school level. We then estimate a binary logit of the probability of staying in the origin on origin log network size, the first stage residual, individual-level controls in lieu of averages from the first stage, and keep all other predictors the same. We report bootstrapped standard errors with 400 reps and cluster resampling at the origin $\times$ school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 5: Effect of Alumni Network Size in City of Displacement on Probability of Staying and Re-Employment with or without Co-Alumni

	Outcome		
	1(Stay)	1(Stay + co-alum at firm 1-yr post-displacement)	1(Stay + no co-alum at firm 1-yr post-displacement)
	(1)	(2)	(3)
log Number of Co-Alumni	0.389***	0.545***	-0.343***
	(0.072)	(0.062)	(0.075)
Inclusive Value	-0.367***	-0.229**	-0.081
	(0.110)	(0.095)	(0.118)
Average Marginal Effect of log Number of Co-Alumni	0.060***	0.111***	-0.048***
	(0.011)	(0.012)	(0.010)
Observations	10,743	10,245	9,633
Individual controls	X	X	X
Layoff year FE	X	X	X
Origin x school strata FE	X	X	X

Notes: Estimates of the impact of log alumni network size in the city of displacement (origin) on the joint probability of staying and finding re-employment with or without a co-alumni. We estimate the second-step logit in Equation 9. Column 1 reports our baseline estimate of β^{Stay}. Dependent variables in columns 2 and 3 are indicators for jointly staying in the same metro and having or not having, respectively, a co-alum at their new firm. Estimation proceeds in two steps. First, we estimate, via Poisson pseudo-maximum likelihood (PPML), the parameters in our gravity equation for destination choice (conditional on moving) in Equation 10. We use these estimates to construct the inclusive value. In our second step, we estimate logits at the worker level. All models include individual controls: gender, race, age and age-squared; fixed effects for the calendar year of displacement; and origin $\times$ school strata fixed effects, where origin refers to the city in which the worker was displaced. School strata are defined as in Data Appendix B.3. Standard errors are bootstrapped, based on 400 reps and cluster resampling at the city $\times$ school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 6: Effect of Alumni Network Size in Destination City on Directed Migration

	Outcome: Number of o to d movers				
	(1)	(2)	(3)	(4)	(5)
Log Alumni Network Size	0.819***	0.837***	0.612***	0.790***	0.907***
	(0.010)	(0.032)	(0.015)	(0.045)	(0.060)
Observations	459,361	51,360	87,142	31,422	17,431
Origin x School FE	X	X	X	X	X
Destination FE	X				
Destination x School Metro FE				X	
Destination x Strata FE		X			X
Origin x Destination FE			X	X	X

Notes: Estimates of $\widetilde{\beta}^{Leave}$, the effect of destination alumni network size on destination choice conditional on moving, from gravity equation (Equation 10) via Poisson pseudo-maximum likelihood (PPML). Dependent variable is the number of displaced alumni from school s in city o who move to a different city d 1 year post-displacement. Primary independent variable is the log alumni network size (for school s) in d. Column 1 includes origin $\times$ school fixed effects and destination fixed effects. Column 2 adds destination $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3. Column 3 replaces destination fixed effects and destination $\times$ strata fixed effects with origin $\times$ destination fixed effects. Column 4 adds destination $\times$ school metro fixed effects, where school metro is the metro of a job seeker's *alma mater*. Column 5 replaces destination $\times$ school metro fixed effects with destination $\times$ school strata fixed effects. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table 7: Effect of Alumni Network Size in Destination City on Directed Migration — Control Function Approach with Instrumental Variable

	Outcome: Number of o to d movers	
	CF+IV	Baseline
	(1)	(2)
Log Alumni Network Size	0.999***	0.907***
	(0.164)	(0.060)
Observations	15,649	17,431
First Stage	2.594***	
	(0.078)	
F-statistic	1,117.5	
Origin x School FE	X	X
Destination x Strata FE	X	X
Origin x Destination FE	X	X

Notes: In column 1, we report our two-stage residual inclusion (2SRI) estimate of $\widetilde{\beta}^{Leave}$, the effect of destination network size on destination choice conditional on moving, using a control function approach with an instrumental variable. We report this estimate alongside our baseline estimate of $\widetilde{\beta}^{Leave}$ Table 6 column 5. Our instrument is $W_{ds} = \frac{Share_{s,1972}}{1+dist_{ds}}$, where $Share_{s,1972}$ is a school's share of in-state students in 1972 and $dist_{ds}$ is the great circle destination-school (excluding origin) distance in miles. In a first stage, destination log network size, averaged across job seekers' years of displacement within origin $\times$ school, is regressed on W_{ds}, $dist_{ds}$, origin $\times$ school fixed effects, origin $\times$ destination fixed effects and destination $\times$ strata fixed effects, where strata are defined as in Data Appendix B.3. There are 399,131 observations at the origin $\times$ destination $\times$ school level in this first stage. First stage standard errors are clustered three ways by origin $\times$ school, origin $\times$ destination, and destination $\times$ school. We then estimate a gravity equation via Poisson pseudo-maximum likelihood (PPML) relating the number of displaced alumni from school s in city o who move to city d 1 year post-displacement to destination log network size, the first stage residual, and the same fixed effects and $dist_{ds}$ from the first stage. PPML drops many separated observations from the first stage. We report bootstrapped standard errors based on 400 reps and cluster resampling at the origin $\times$ school level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 8: Effect of Destination Alumni Network Size on Directed Migration for Job Seekers Who Move and are Re-employed with Versus without Co-alumni at New Firm

	Outcome		
	Number of o to d movers	Number of o to d movers w/ co-alum	Number of o to d movers w/o co-alum
	(1)	(2)	(3)
Log Alumni Network Size	0.907***	1.168***	0.564***
	(0.060)	(0.123)	(0.153)
Observations	17,431	6,100	2,034
Origin x Destination FE	X	X	X
Origin x School FE	X	X	X
Destination x Strata FE	X	X	X

Notes: Estimates of $\widetilde{\beta}^{Leave}$, the effect of destination alumni network size on destination choice conditional on moving, from gravity equation (Equation 10) via Poisson pseudo-maximum likelihood (PPML), separately for workers re-employed with or without a co-alumni at their new firm. Dependent variable in column 1 is the number of displaced alumni from school s in city o who move to a different city d 1 year post-displacement. Dependent variables in columns 2 and 3 are the number of alumni from school s who move from o to d and are also re-employed with or without, respectively, a co-alumni at their firm 1 year post-displacement. Primary independent variable is the log alumni network size (for school s) in city d. All columns include origin $\times$ destination pair fixed effects, origin $\times$ school fixed effects, and destination $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table 9: Effect of Same-Industry Alumni Network Size in Destination City on Directed Migration

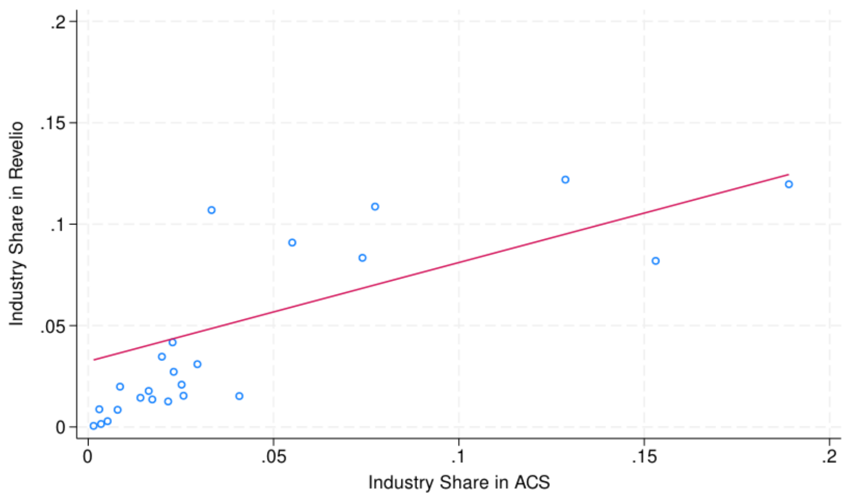
	Outcome: Number of o to d movers		
	(1)	(2)	(3)
Log Alumni Network Size	0.636***	0.873***	0.787***
	(0.017)	(0.088)	(0.267)
Observations	70,458	10,417	7,386
Origin x School x Industry FE	X	X	X
Origin x Destination FE	X	X	X
Destination x Industry FE	X		X
Destination x School FE		X	X

Notes: Estimates of $\widetilde{\beta}^{Leave}$, the effect of same-industry alumni network size in a destination on the destination choice conditional on moving. We estimate our gravity equation (Equation 14) via PPML, with data collapsed to the origin $\times$ destination $\times$ school $\times$ industry level. Dependent variable is the number of alumni from school s who are displaced in city o and industry j and move to a different city d 1 year post-displacement. Primary independent variable is the log number of alumni (for school s) in d for a given industry j. All models include origin $\times$ school $\times$ industry fixed effects and origin $\times$ destination pair fixed effects. Column 1 also adds destination $\times$ industry fixed effects. Column 2 replaces destination $\times$ industry fixed effects with destination $\times$ school fixed effects. Column 3 includes both destination $\times$ industry fixed effects and destination $\times$ school fixed effects. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

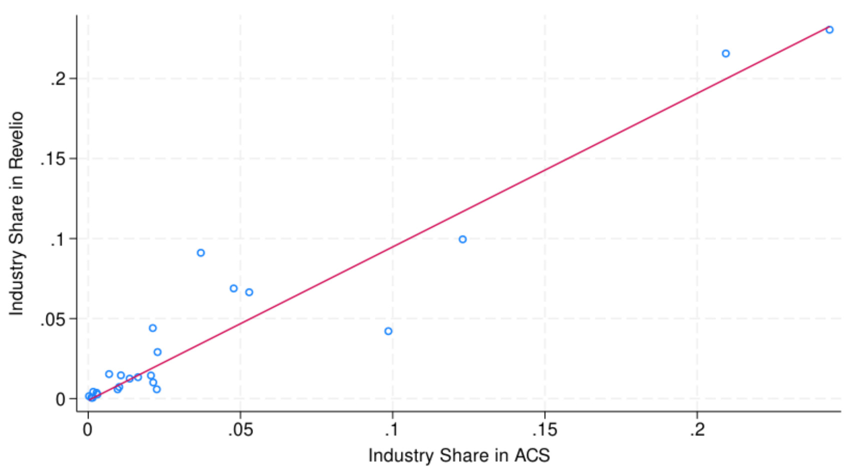
A Appendix Figures and Tables

A.1 Appendix Figures

Figure A.1: Pooled 2010-2019 Industry Shares for Prime-Age College-Educated Workers, Revelio vs. IPEDS



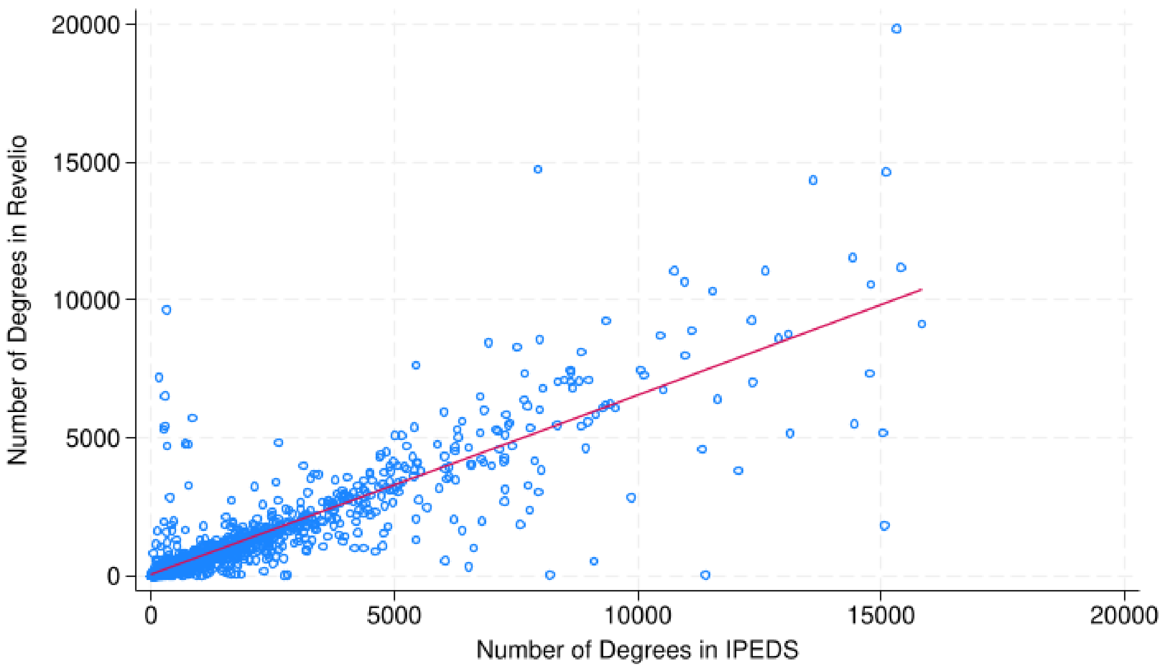
(a) National



(b) Washington DC

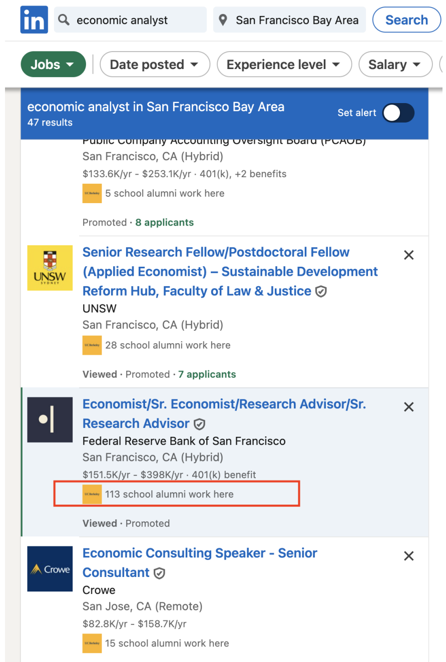
Notes: Plots of industry mix in Revelio vs. ACS, nationwide (top panel) and Washington DC only (bottom panel). The vertical axis reports the pooled share of jobs held by college-educated workers aged 25-54 in a given 2-digit NAICS industry observed in 2010-2019 in the Revelio Labs data (including all workers, not just those displaced in mass layoffs or firm closures). Each job is only counted once, even if active for multiple consecutive years in the 2010-2019 timeframe. The horizontal axis reports the same share in the ACS, pooling the 2010-2019 cross sections. Each point represents a unique 2-digit NAICS code.

Figure A.2: Average Yearly Degrees Awarded from 2010-2019, Revelio vs. IPEDS

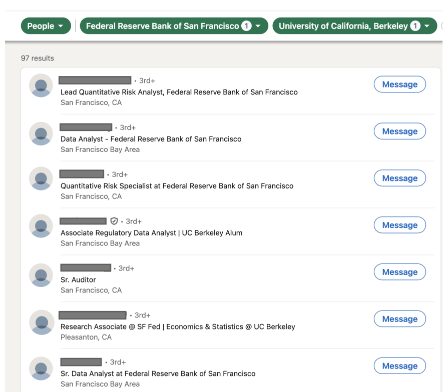


Notes: The vertical axis reports the average yearly number of degrees (all degrees) from 2010-2019 observed for each 4-year institution in our data on self-reported educational histories in LinkedIn. The horizontal axis reports the average yearly number of degrees (all degrees) for each 4-year institution as reported in the IPEDS 2010-2019 completions data files.

Figure A.3: A College-Educated Job Seeker on LinkedIn Can Access Many Pieces of Information about a Local Alumni Network



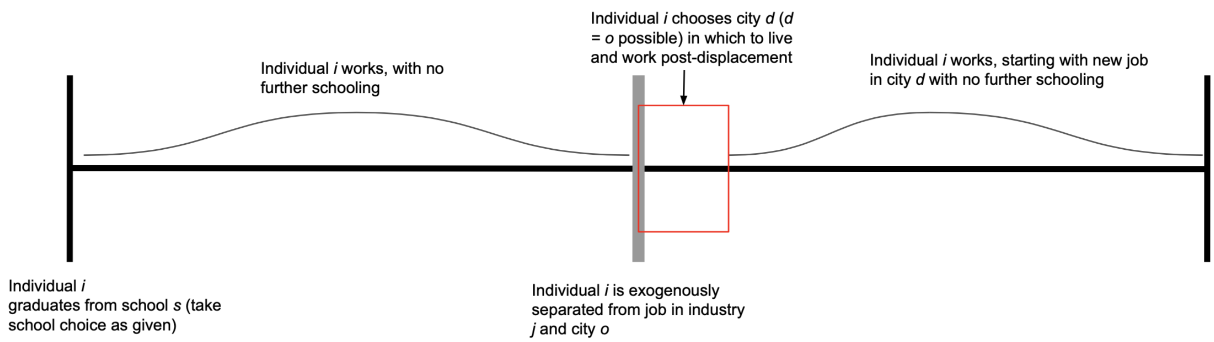
(a) Job Search Page



(b) List of Co-Alumni at Highlighted Job

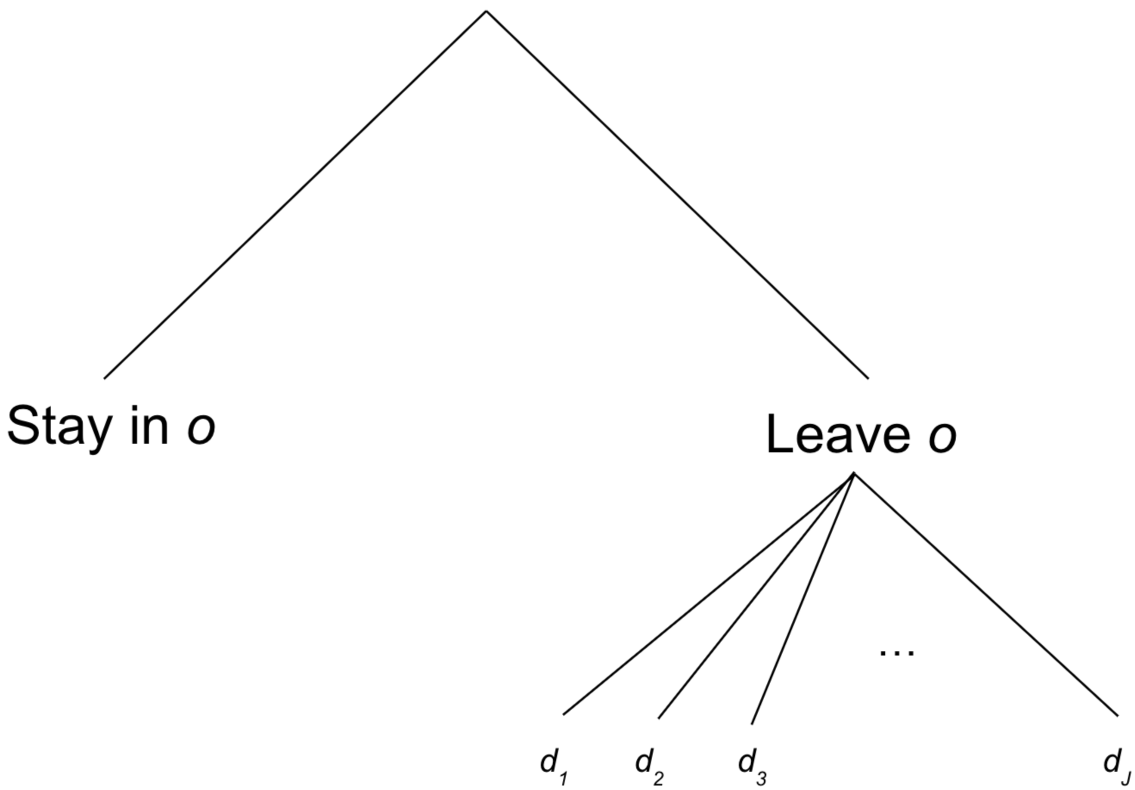
Notes: The top panel displays a present-day snapshot of LinkedIn's job search tool from the perspective of a user. The user can highlight a specific local labor market and see not only a list of relevant jobs in that local labor market, but also the number of co-alumni who work there. In the bottom panel, we highlight the page that shows the full list of co-alumni after a user has clicked on the number of co-alumni button in the top panel. LinkedIn's job search tool and related tools have been in place since the early 2010s, so this feature is directly relevant for our sample of job seekers.

Figure A.4: Job Seeker's Location Choice Decision in Work History Timeline



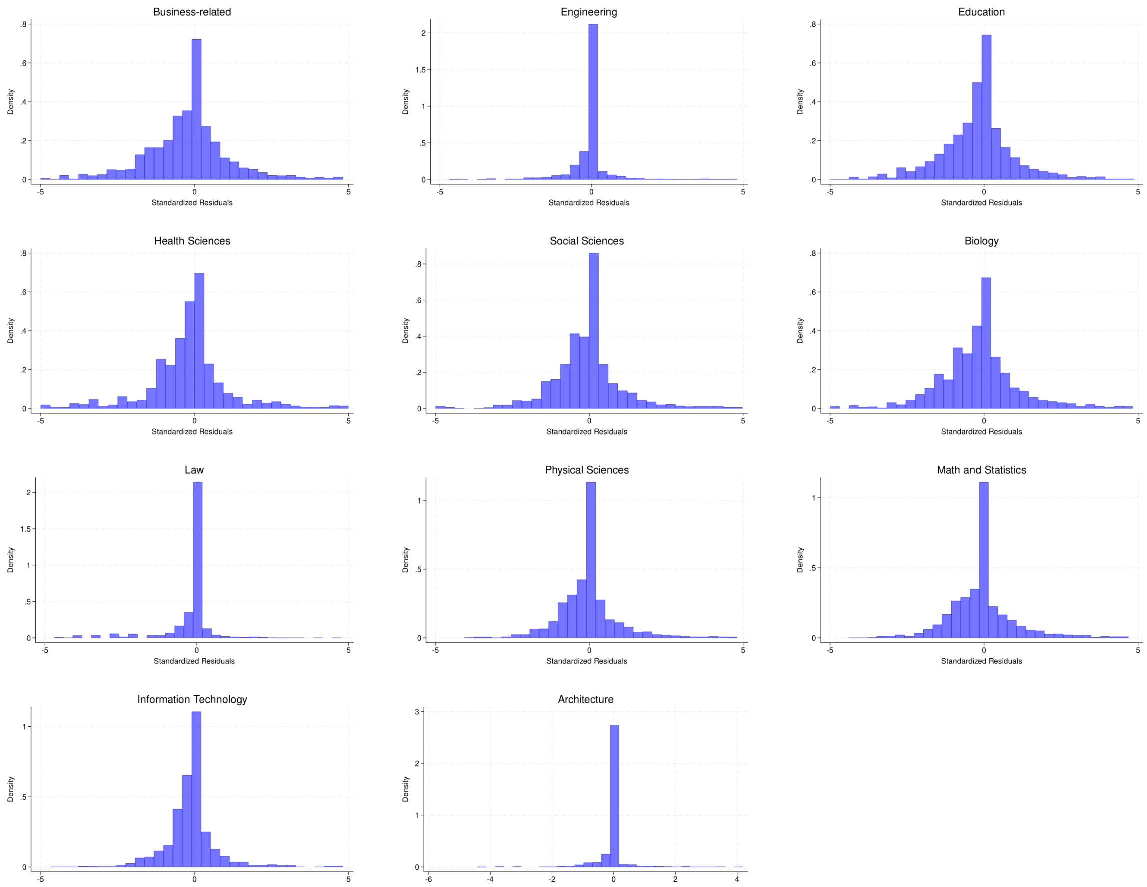
Notes: This diagram traces a worker's post-graduation work history, excluding any job spells that happened before the worker's receipt of highest degree. School choice is taken as given. Otherwise, we focus on the location and job choice in the red outline, immediately following exogenous separation from their previous job due to a mass layoff or firm closure.

Figure A.5: Job Seeker's Location Decision Tree



Notes: This diagram traces a displaced job seeker's location decision tree in our model. The job seeker decides whether or not to stay in the city of displacement, and if they leave, then they choose among all remaining alternative destinations.

Figure A.6: Predictive Accuracy of School Strata in Explaining School Major Share



Notes: Data from IPEDS 2010 completions, at the school level. We plot histograms of standardized residuals from a regression of the share of Bachelor's+ degree recipients in 2010 from each major (2-digit CIP code) at a school on school strata fixed effects, where school strata are defined as in the Data Appendix Section B.3. The eleven majors displayed here correspond to the observed majors, with appropriate aggregation for consistency with 2-digit CIP codes, in the Revelio Labs data. From top left to bottom right, we report the majors in descending order of their frequency in Revelio Labs, with Business-related (which is an aggregate of Business, Finance, Accounting and Marketing) as the most common major, and Information Technology as the least common. We have 1,840 schools and 431 school strata. Regressions are weighted by the number of degrees a school awarded in 2010.

A.2 Appendix Tables

Table A.1: Variation in School Major Share Explained by School Strata

Major	R-squared
Business-related	0.40
Engineering	0.41
Education	0.48
Health Sciences	0.48
Social Sciences	0.57
Biology	0.49
Law	0.32
Physical Sciences	0.52
Math and Statistics	0.48
Information Technology	0.33
Architecture	0.41

Notes: Data from IPEDS 2010 completions, at the school level. We report the R-squared from a regression of the share of Bachelor's+ degree recipients in 2010 from each major (2-digit CIP code) at a school on school strata fixed effects, where school strata are defined as in the Data Appendix Section B.3. The eleven majors displayed here correspond to the observed majors, with appropriate aggregation for consistency with 2-digit CIP codes, in the Revelio Labs data. We report the majors in descending order of their frequency in Revelio Labs, with Business-related (which is an aggregate of Business, Finance, Accounting and Marketing) as the most common major, and Information Technology as the least common. We have 1,840 schools and 431 school strata. Regressions are weighted by the number of degrees a school awarded in 2010.

Table A.2: Effect of Alumni Network Size in Destination City on Location Choice from Multinomial Logit Framework

	Outcome: Number of o to d movers				
	(1)	(2)	(3)	(4)	(5)
Log Alumni Network Size	1.013***	0.976***	0.975***	0.461***	0.561***
	(0.020)	(0.011)	(0.026)	(0.013)	(0.036)
Observations	890,960	872,900	163,089	135,067	56,872
Origin x School FE	X	X	X	X	X
Destination FE		X			
Destination x Strata FE			X		X
Origin x Destination FE				X	X

Notes: Estimates of the effect of alumni network size in any city on city choice using a multinomial logit alternative to our nested logit model. Estimates from gravity equation (Equation 10) via PPML, run on full counts for both movers and stayers. Dependent variable is the number of displaced alumni from school s in city o who choose city d, with $d = o$ possible, 1 year post-displacement. Primary independent variable is the log alumni network size (for school s) in d. Column 1 includes origin $\times$ school fixed effects. Column 2 adds destination fixed effects. Column 3 replaces destination fixed effects with destination $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3, whereas column 4 instead includes origin $\times$ destination fixed effects. Column 5 includes both. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.3: Effect of Destination-Origin Difference in Alumni Network Size on Directed Migration

	Outcome: $\log(\frac{\text{Number of o to d movers}}{\text{Number of stayers in o}})$			
	(1)	(2)	(3)	(4)
Difference in Alumni Network Size	0.405***	0.402***	0.330***	0.449***
	(0.020)	(0.017)	(0.023)	(0.026)
Observations	6,333	6,317	5,622	1,064
Origin FE	X	X		
Destination FE	X	X		
School FE		X	X	
Origin x Destination FE			X	X
Destination x School FE				X

Notes: Estimates from log-odds gravity equation, mirroring Moretti and Wilson (2017), via OLS. Dependent variable is the log ratio of the following: in the numerator, the number of displaced alumni from school s in city o who move to city d 1 year post-displacement; in the denominator, the number of displaced alumni from school s in city o who stay in o. Primary independent variable is the difference in the log alumni network size (for school s) between d and o. Column 1 includes origin and destination fixed effects. Column 2 adds school fixed effects. Columns 3-4 replace separate origin and destination fixed effects with origin $\times$ destination pair fixed effects. Column 4 replaces school fixed effects with destination $\times$ school fixed effects. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.4: Effect of Alumni Network Size (of Bachelor's Institution) in City of Displacement on Probability of Staying

	Outcome: 1(Stay metro 1-year post-displacement)		
	(1)	(2)	(3)
log Number of Co-Alumni	0.325***	0.416***	0.348***
	(0.014)	(0.064)	(0.075)
Inclusive Value	-0.492***	-0.348***	-0.264**
	(0.045)	(0.083)	(0.127)
Observations	17,470	13,014	10,820
Individual controls	X	X	X
Institutional controls	X	X	
Layoff year FE	X	X	X
Origin FE	X		
Origin x school metro FE		X	
Origin x school strata FE			X

Notes: Notes: Table notes are the same as those for Table 2. The difference here is that network and school definitions are now based on the institution of Bachelor's degree, and not of highest completion.

Table A.5: Effect of Alumni Network Size (of Bachelor's Institution) in Destination City on Directed Migration

	Outcome: Number of o to d movers				
	(1)	(2)	(3)	(4)	(5)
Log Alumni Network Size	0.818***	0.834***	0.609***	0.799***	0.910***
	(0.010)	(0.031)	(0.015)	(0.043)	(0.061)
Observations	458,065	50,886	87,107	31,329	17,232
Origin x School FE	X	X	X	X	X
Destination FE	X				
Destination x School Metro FE				X	
Destination x Strata FE		X			X
Origin x Destination FE			X	X	X

Notes: Table notes are the same as those for Table 6. The difference here is that network and school definitions are now based on the institution of Bachelor's degree, and not of highest completion.

Table A.6: Effect of Alumni Network Size in City of Displacement on Probability of Staying for Workers Displaced Outside of Home City

	Outcome: 1(Stay metro 1-year post-displacement)		
	(1)	(2)	(3)
log Number of Co-Alumni	0.350***	0.347***	0.354***
	(0.021)	(0.057)	(0.074)
Inclusive Value	-0.521***	-0.187**	-0.267***
	(0.054)	(0.086)	(0.100)
Observations	11,842	7,512	5,895
Individual controls	X	X	X
Institutional controls	X	X	
Layoff year FE	X	X	X
Origin FE	X		
Origin x school metro FE		X	
Origin x school strata FE			X

Notes: Table notes are the same as those for Table 2. Model estimated on subset of job seekers who are displaced in a metro that is different from the metro in which they obtained their highest degree. Standard errors not yet adjusted for sampling variability in the inclusive value. Bootstrapped standard errors are roughly twice as large, based on our other models.

Table A.7: Effect of Destination Alumni Network Size on Directed Migration for Workers Displaced Outside of Home City

	Outcome: Number of o to d movers				
	(1)	(2)	(3)	(4)	(5)
Log Alumni Network Size	0.775***	0.819***	0.629***	0.847***	0.880***
	(0.011)	(0.038)	(0.015)	(0.066)	(0.078)
Observations	398,978	41,555	69,021	21,119	12,051
Origin x School FE	X	X	X	X	X
Destination FE	X				
Destination x School Metro FE				X	
Destination x Strata FE		X			X
Origin x Destination FE			X	X	X

Notes: Table notes are the same as those for Table 6. Model estimated on subset of job seekers who are displaced in a metro that is different from the metro in which they obtained their highest degree.

Table A.8: Effect of Alumni Network Size in Destination City on Directed Migration for Workers who are Displaced Outside of Home City and Do Not Return to Home City

	Outcome: Number of o to d movers			
	(1)	(2)	(3)	(4)
Log Alumni Network Size	0.595***	0.530***	0.411***	0.371***
	(0.013)	(0.043)	(0.019)	(0.105)
Observations	341,948	35,640	55,740	9,129
Origin x School FE	X	X	X	X
Destination FE	X			
Destination x Strata FE		X		X
Origin x Destination FE			X	X

Notes: Table notes are the same as those for Table 6. Model estimated on subset of job seekers who are displaced in a metro that is different from the metro in which they obtained their highest degree, additionally excluding workers who move back to the metro of their school 1 year post-displacement.

Table A.9: Estimated Impact of Alumni Network Size in City of Displacement on Probability of Staying is Robust to Including Location-Specific Demographic Heterogeneity

	Outcome: 1(Stay metro 1-year post-displacement)	
	(1)	(2)
log Number of Co-Alumni	0.446***	0.755***
	(0.065)	(0.117)
Outside Option Value	-0.056*	-0.116
	(0.032)	(0.128)
Observations	5,788	2,625
Individual controls	X	X
Layoff year FE	X	X
Origin x school strata FE	X	
Origin x dem group FE	X	
Origin x school strata x dem group FE		X

Notes: Table notes are the same as those for Table 2, other than differences in the fixed effects included across specifications. Individual controls are age and age-squared — ethnicity and gender are absorbed by our definition of demographic groups below. Column 1 adds origin $\times$ demographic group FE to our baseline model in column 3 of Table 2. Demographic groups are defined as one of 12 groups based on the interaction of: gender (male or female), age bracket (22-30, 31-39, 40+) and race (white or non-white). Column 2 replaces origin $\times$ demographic group fixed effects with fully interacted origin $\times$ demographic group $\times$ strata fixed effects. Standard errors are clustered at the origin $\times$ school level but not yet adjusted for sampling variability in the inclusive value. Bootstrapped standard errors are roughly twice as large, based on our other models. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.10: Inclusion of Location-Specific Demographic Heterogeneity Does Not Impact Estimated Effect of Alumni Network Size in Destination City on Directed Migration

	Outcome: Number of o to d movers in School s and Demographic group g			
	(1)	(2)	(3)	(4)
Log Alumni Network Size	0.901***	1.116***	1.044***	0.996***
	(0.058)	(0.077)	(0.140)	(0.172)
Observations	27,966	24,605	5,663	2,928
Origin x School x Dem Group FE	X	X	X	X
Destination x Strata FE	X	X	X	
Origin x Destination FE	X	X		X
Destination x Dem Group FE		X		
Origin x Destination x Dem Group FE			X	
Destination x Strata x Dem Group FE				X

Estimates from adapted version of gravity equation (Equation 10) via PPML. Dependent variable is now counts of o to d movers (1-year post-displacement) in a origin-school-demographic group (g) combination, where $d \neq o$ and data is collapsed to the $o \times d \times s \times g$ level. Demographic groups are defined as one of 12 groups based on the interaction of: gender (male or female), age bracket (22-30, 31-39, 40+) and race (white or non-white). Primary independent variable is the log alumni network size (for school s) in d. All columns include origin $\times$ school $\times$ demographic group fixed effects. Columns 1 and 2 include origin $\times$ destination fixed effects and destination $\times$ strata fixed effects, where strata are defined as in Data Appendix B.3. Column 2 adds destination $\times$ demographic group fixed effects to column 1. Column 3 replaces origin $\times$ destination fixed effects and destination $\times$ demographic group fixed effects with fully interacted origin $\times$ destination $\times$ demographic group fixed effects. Column 4 returns to including origin $\times$ destination fixed effects but replaces destination $\times$ strata fixed effects with fully interacted destination $\times$ strata $\times$ demographic group fixed effects. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.11: Estimated Impact of Alumni Network Size in City of Displacement on Probability of Staying is Robust to Exploiting Narrower Variation Within Firm-Strata

	Outcome: 1(Stay metro 1-year post-displacement)	
	(1)	(2)
log Number of Co-Alumni	0.389***	0.537***
	(0.072)	(0.105)
Inclusive Value	-0.367***	-0.368**
	(0.110)	(0.146)
Observations	10,743	2,143
Individual controls	X	X
Layoff year FE	X	X
Origin x school strata FE	X	
Firm x school strata FE		X

Notes: Table notes are the same as those for Table 2, other than differences in the fixed effects included across specifications. Column 1 replicates the specification from column 3 of Table 2. Column 2 replaces origin $\times$ strata fixed effects with interacted firm $\times$ strata fixed effects, e.g. Microsoft Seattle $\times$ strata, where a firm nests both origin and company. Standard errors not yet adjusted for sampling variability in the inclusive value. Bootstrapped standard errors are roughly twice as large, based on our other models. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.12: Inclusion of Firm-Specific Heterogeneity Does Not Impact Estimated Effect of Alumni Network Size in Destination City on Directed Migration

	Outcome: Number of o to d movers in School s and Firm f		
	(1)	(2)	(3)
Log Alumni Network Size	0.903***	0.907***	0.855***
	(0.059)	(0.147)	(0.146)
Observations	27,700	3,590	3,013
School x Firm FE	X	X	X
Destination x Strata FE	X	X	X
Origin x Destination FE	X	X	
Destination x Company FE		X	
Destination x Firm FE			X

Estimates from adapted version of gravity equation (Equation 10) via PPML. Dependent variable is now counts of o to d movers (1-year post-displacement) in a school-firm (f) combination, where $d \neq o$ and data is collapsed to the $d \times s \times f$ level. Firms nest the city of displacement o (company $\times$ o). Primary independent variable is the log alumni network size (for school s) in d. All columns include school $\times$ firm fixed effects. All columns also include destination $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3. Columns 1 and 2 include origin $\times$ destination fixed effects. Column 2 adds destination $\times$ company fixed effects to column 1. Column 3 replaces destination $\times$ company fixed effects with destination $\times$ firm fixed effects, which absorbs all factors varying at the origin $\times$ destination level. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.13: Controlling for Major Does Not Affect Estimated Effect of Alumni Network Size in City of Displacement on Probability of Staying

	Outcome: 1(Stay metro 1-year post-displacement)		
	Logit	LPM	
	(1)	(2)	(3)
log Number of Co-Alumni	0.442***	0.069***	0.089***
	(0.057)	(0.011)	(0.013)
Inclusive Value	-0.200***	-0.029**	-0.011
	(0.077)	(0.013)	(0.033)
Average Marginal Effect of	0.071***	0.069***	0.089***
log Number of Co-Alumni	(0.009)	(0.011)	(0.013)
Observations	7,976	8,430	8,167
Individual controls	X	X	X
Layoff year FE	X	X	X
School FE			X
Origin x School Strata FE	X	X	
Origin x Major FE	X	X	
Origin x Major x school strata FE			X

Notes: Estimates from second-step logit and LPM approximations in Equation 9, with additional major-specific heterogeneity. Dependent variable is an indicator for whether a displaced worker stays in the same metro 1 year post-displacement. Estimation proceeds in two steps. In a first step, we estimate the parameters in our choice probability model (Equation 8b) using our gravity equation for destination choice (conditional on moving) in Equation 10. We add destination $\times$ major fixed effects to the gravity equation. We use these estimates to construct the inclusive value. In our second step, we estimate logits and LPMs at the worker level. All models include fixed effects for the calendar year of displacement and individual controls: gender, race, age and age-squared. In columns 1 and 2 we include origin $\times$ school strata fixed effects and origin $\times$ major fixed effects, with column 1 estimating a logit and column 2 the LPM. School strata are defined as in Data Appendix B.3. We define major based on the primary major at institution of highest degree, and include a separate category for missing majors. In column 3, we estimate an LPM equivalent to column 2 but add school fixed effects and fully interacted origin $\times$ major $\times$ strata fixed effects. Standard errors are clustered at the origin $\times$ school level but not yet adjusted for sampling variability in the inclusive value. Bootstrapped standard errors are roughly twice as large, based on our other models. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.14: Inclusion of Major-Specific Heterogeneity Does Not Impact Estimated Effect of Alumni Network Size in Destination City on Directed Migration

	Outcome: Number of o to d movers in School s and Major m			
	(1)	(2)	(3)	(4)
Log Alumni Network Size	0.808***	0.606***	0.887***	0.964***
	(0.036)	(0.016)	(0.063)	(0.073)
Observations	60,872	78,947	22,130	19,867
Origin x School x Major FE	X	X	X	X
Destination x Strata FE	X		X	X
Origin x Destination FE		X	X	X
Destination x Major FE				X

Estimates from adapted version of gravity equation (Equation 10) via PPML. Dependent variable is now counts of o to d movers (1-year post-displacement) in not just a school s but school-major (m) combination, where data is collapsed to the $o \times d \times s \times m$ level. Primary independent variable is the log alumni network size (for school s) in d. Column 1 includes origin $\times$ school $\times$ major fixed effects and destination $\times$ school strata fixed effects, where strata are defined as in Data Appendix B.3. Column 2 replaces destination $\times$ strata fixed effects with origin $\times$ destination fixed effects. Column 3 includes both. Column 4 adds destination $\times$ major fixed effects. Standard errors are clustered three-ways at the origin $\times$ destination, origin $\times$ school, and destination $\times$ school levels. Significance levels: * 10%, ** 5%, and *** 1%.

Table A.15: Effect of Alumni Network Size (2010-2019 Yearly Average) in City of Displacement on Probability of Staying

	Outcome: 1(Stay metro 1-year post-displacement)		
	(1)	(2)	(3)
log Number of Co-Alumni	0.324***	0.415***	0.378***
	(0.018)	(0.081)	(0.097)
Inclusive Value	-0.491***	-0.375***	-0.365***
	(0.050)	(0.093)	(0.112)
Observations	17,435	12,943	10,743
Individual controls	X	X	X
Institutional controls	X	X	
Layoff year FE	X	X	X
Origin FE	X		
Origin x school metro FE		X	
Origin x school strata FE			X

Notes: Table notes are the same as those for Table 2. We use a different measure of alumni network size relative to our baseline, namely the log yearly average (from 2010-2019) number of alumni in the city of displacement.

Table A.16: Effect of Alumni Network Size (2010-2019 Yearly Average) in Destination City on Directed Migration

	Outcome: Number of o to d movers				
	(1)	(2)	(3)	(4)	(5)
Log Alumni Network Size	0.821***	0.846***	0.614***	0.795***	0.905***
	(0.010)	(0.032)	(0.015)	(0.045)	(0.060)
Observations	455,780	51,357	86,973	31,396	17,431
Origin x School FE	X	X	X	X	X
Destination FE	X				
Destination x School Metro FE				X	
Destination x Strata FE		X			X
Origin x Destination FE			X	X	X

Notes: Table notes are the same as those for Table 6. We use a different measure of alumni network size relative to our baseline, namely the log yearly average (from 2010-2019) number of alumni in the potential destination city.

B Data Appendix

B.1 Mass Layoffs and Firm Closures Definition

From Revelio Labs' yearly Workforce Dynamics files from 2010-2018, we use monthly changes in employment counts at the firm $\times$ month level to define mass layoff and firm closure events. Our approach closely follows Schmieder, Von Wachter and Heining (2023). For mass layoff events, we impose the following set of criteria, all of which must be satisfied. First, the firm experienced a 30% year-to-year drop in employment, a 30% 1-month drop, or a 1-month drop of 500+ employees. Second, the firm had at least 25 employees in the prior month or year. Third, employment at the firm did not increase by more than 30% in the 2 years preceding the employment drop, and did not increase by 30% in the 2 ensuing years. Finally, no more than 20% of the laid-off employees were re-employed at the same firm within 1 year after the layoff event.

Our criteria to define firm closure events is as follows. First, the firm must have experienced a 80% year-to-year drop in employment, or 80% 1-month drop in employment. Second, the firm must have had at least 3 employees in the prior month or year. Finally, no more than 20% of the displaced employees at the firm are re-employed at the same firm within 1 year after the closure event.

B.2 Data on Individual Characteristics

For all workers in the individual job histories file observed in the US between 2010 and 2019, we also have imputed demographic characteristics from user names reported on their LinkedIn profiles. Revelio Labs estimates the probability that a user is male or female based on their first name and its share of each gender in social security administration data, from which we impute the user's gender. We identify male users as those with a male probability exceeding 0.5, and female users as those with a female probability exceeding 0.5. We also impute each user's ethnicity from estimated probabilities that the user is Black, Hispanic, White, Asian-Pacific Islander, Native American, or multiple races. These estimated probabilities come from Revelio Labs' model predicting ethnicity using first name, last name, and location in US Census data. For each user, we assign the ethnicity with the highest estimated probability. Additional variables that reveal more information on a given user's activity on the LinkedIn platform are the date that the profile was last refreshed as well as the user's number of LinkedIn connections on this date. We do not, however, observe to whom a user is connected and thus cannot identify information about the composition of users' networks of personal connections.

B.3 Coarsened Exact Matching of Schools

We compare the relative local alumni network sizes of observably similar schools located in the same geographical area. To create groups of observably similar schools, which we call our school strata, we use coarsened exact matching (CEM) on several school characteristics observed in 2010 IPEDS data (Blackwell et al. 2009).

We start by defining location zones to ensure that all schools in the same school strata are in the same location zone. Our location zones are defined either as populous cities with many schools, e.g. Boston and Chicago, populous states, e.g. Texas, or small groups of adjacent non-populous states, e.g. North Dakota and South Dakota combined. Within each location zone, we use CEM to create strata based on binned versions of the following school characteristics in 2010: school size (4 bins), admissions rate (3 bins), 75th percentile composite SAT score (4 bins), and share of enrolled freshmen that are in-state (2 bins).

For a minority of colleges and universities, an exact match on the four aforementioned characteristics does not exist within their location zone. In these instances, we standardize these characteristics and assign these schools to the strata to which their nearest neighbor in the same location zone, based on minimum Mahalanobis distance, belongs. Or in the common event two schools are each other's nearest neighbor and no one else's, we create a new strata for those two schools.

We end up with 431 strata for 1,840 4-year colleges and universities (402 strata for 1,399 schools in our estimation sample). Some examples are as follows. In New England, we have a strata that consists solely of highly selective liberal arts colleges located outside of Boston: Middlebury, Bowdoin, Williams, Amherst, and Wesleyan. We have another strata that consists solely of large public universities in Arizona: University of Arizona and Arizona State University. And as a final example, we have a strata that consists solely of universities located in Northern California that are part of the California State University system: Cal State Chico, Cal State Fresno, and Cal State Sacramento.

C Model Derivations

C.1 Impact of Origin Network Size on Probability of Staying

We show that an increase in the number of co-alumni in the city of displacement, σ_{os}, increases the probability of staying if $\beta^{Stay} > 0$. We start with a restatement of Equation 7b, the choice probability for staying in the origin:

$$Pr(Stay_{ios}) = \frac{\exp\left[\overbrace{(\omega^{Stay} + \rho^{Stay})}^{\equiv \beta^{Stay}} \log(\sigma_{os}) + \overbrace{(A_{os} + Z_{os}) + (B_o^{City} - r_o) + X_i'\eta}^{\equiv H_{ios}}\right]}{\exp\left[\underbrace{(\omega^{Stay} + \rho^{Stay})}_{\equiv \beta^{Stay}} \log(\sigma_{os}) + \underbrace{(A_{os} + Z_{os}) + (B_o^{City} - r_o) + X_i'\eta}_{\equiv H_{ios}}\right] + \exp(\lambda IV_{os})} \tag{15}$$

where we use H_{ios} to simplify notation by aggregating terms that do not include σ_{os}. If we use the quotient rule and take the partial derivative of $Pr(Stay_{ios})$ with respect to σ_{os}, we obtain:

$$\frac{\partial Pr(Stay_{ios})}{\partial \sigma_{os}} = \frac{\overbrace{\exp(\lambda IV_{os})}^{+} \left(\beta^{Stay} \, \overbrace{\sigma_{os}^{\beta^{Stay}-1} \exp(H_{ios})}^{+ \text{ if } \sigma_{os}>0}\right)}{\underbrace{\left(\exp\left[\beta^{Stay} \log(\sigma_{os}) + H_{ios}\right] + \exp(\lambda IV_{os})\right)^2}_{+}} \tag{16}$$

Recall that $IV_{os} \equiv \log(\sum_{m=1}^{J\setminus\{o\}} \exp(\frac{V_{ioms}}{\lambda}))$. Because the inner summation is over all destinations *excluding* o, the origin network size σ_{os} never appears in V_{ioms} for any $m \neq o$. Thus when taking the partial derivative of $Pr(Stay_{ios})$ with respect to σ_{os}, the inclusive value of the *Leave* nest IV_{os} can be treated as a constant. Because the denominator of the partial derivative in Equation 16 is a squared term, it is always positive. In the numerator, we note that $\exp(H_{ios})$ and $\exp(\lambda IV_{os})$ are always positive. For any $\sigma_{os} > 0$, we also have that $\sigma_{os}^{\beta^{Stay}-1} > 0$ for any value of β^{Stay}. Thus with only β^{Stay} in the numerator still unaccounted for, the sign of the partial derivative of $Pr(Stay_{ios})$ with respect to origin network size, $\frac{\partial Pr(Stay_{ios})}{\partial \sigma_{os}}$, has the same sign as β^{Stay}. Thus if β^{Stay} is positive (negative), an increase in origin network size increases (decreases) a job seeker's probability of choosing to stay.

C.2 Impact of Destination Network Size on Conditional Destination Choice Probability

Now we show that if $\widetilde{\beta}^{Leave}$ is positive, then an increase in any destination's network size will increase the job seeker's probability of choosing that destination, conditional on moving. We restate, with algebraic simplifications, the destination choice probability, conditional on moving, from Equation 8b:

$$Pr(h_{iods}|Leave) = \frac{\exp\left[\widetilde{\beta}^{Leave}\log(\sigma_{ds}) + \overbrace{\frac{1}{\lambda}\Big((A_{ds}+Z_{ds}) + (B_d^{City} - r_d) - \widetilde{C}_{od}\Big)}^{\equiv H_{ods}}\right]}{\sum_{m=1}^{J\setminus\{o\}} \exp\left[\widetilde{\beta}^{Leave}\log(\sigma_{ms}) + \underbrace{\frac{1}{\lambda}\Big((A_{ms}+Z_{ms}) + (B_m^{City} - r_m) - \widetilde{C}_{om}\Big)}_{\equiv H_{oms}}\right]} \tag{17}$$

where we use H_{ods} and H_{oms} to simplify notation and collect terms that do not feature destination network size σ_{ms} for any $m \neq o$. Using the quotient rule to take the partial derivative of $Pr(h_{iods}|Leave)$ with respect to σ_{ds} for some destination d, we have:

$$\frac{\partial Pr(h_{iods}|Leave)}{\partial \sigma_{ds}} = \frac{\overbrace{\Big(\sum_{m=1}^{J\setminus\{o,d\}} \exp\left[\widetilde{\beta}^{Leave}\log(\sigma_{ms}) + H_{oms}\right]\Big)}^{+} \overbrace{\exp\left[H_{ods}\right]}^{+} \widetilde{\beta}^{Leave} \overbrace{\sigma_{ds}^{\widetilde{\beta}^{Leave}-1}}^{+ \text{ if } \sigma_{ds}>0}}{\underbrace{\Big(\sum_{m=1}^{J\setminus\{o\}} \exp\left[\widetilde{\beta}^{Leave}\log(\sigma_{ms}) + H_{oms}\right]\Big)^2}_{+}} \tag{18}$$

Because the denominator in Equation 18 is a squared term, it is always positive. In the numerator, we have a sum of exponentiated terms, which is always positive since exponentiated terms are themselves positive. Likewise, $\exp[H_{ods}]$ is always positive. If $\sigma_{ds} > 0$, then we also have $\sigma_{ds}^{\widetilde{\beta}^{Leave}-1} > 0$ regardless of the sign of $\widetilde{\beta}^{Leave}$. Thus the sign of $\frac{\partial Pr(h_{iods}|Leave)}{\partial \sigma_{ds}}$ depends entirely on the sign of $\widetilde{\beta}^{Leave}$. If $\widetilde{\beta}^{Leave} > 0$, then we will also have that $\frac{\partial Pr(h_{iods}|Leave)}{\partial \sigma_{ds}} > 0$. Thus an increase in the network size of a destination increases the probability of choosing that destination.

D Additional Notes for Empirical Exercises

D.1 Control Function Approach with Historical Instrumental Variables

In Section 4.2, we present two instrumental variables that isolate arguably exogenous variation in alumni network size that comes from historical differences in in-state enrollment share between schools in the same strata. We employ these instruments in a control function approach to estimate β^{Stay} and $\widetilde{\beta}^{Leave}$. Our two instruments, one for alumni network size in the origin and the other for alumni network size in a destination, are as follows:

$$W_{os} \equiv \frac{Share_{s,1972}}{1 + dist_{os}} \tag{19a}$$

$$W_{ds} \equiv \frac{Share_{s,1972}}{1 + dist_{ds}} \tag{19b}$$

where $Share_{s,1972}$ is the share of enrolled students at school s in 1972 who are from the same state in which s is located. This share is interacted with inverse distance, $\frac{1}{1+dist_{ms}}$ for either $m = o$ or $m = d$, where $dist_{ms}$ is the great circle distance (in miles) between school s and city m. To estimate our two parameters, we estimate linear first stage equations and specify linear control functions in a two-stage residual inclusion (2SRI) procedure (Terza et al. 2008). We first describe the 2SRI estimate of $\widetilde{\beta}^{Leave}$, which we use to then estimate β^{Stay} via 2SRI. We treat $\log(\sigma_{ds(o)})$, the log number of co-alumni from s in a destination d (averaged across the years of displacement of job-seeking alumni from s who are displaced in o), as our potentially endogenous regressor.[53] Our first stage regresses $\log(\sigma_{ds(o)})$ on the instrument W_{ds} and the same fixed effects that are included in our baseline gravity equation in Equation 10. We also add $dist_{ds}$ as a regressor. Thus the linear first stage for our directed migration analysis is:

$$\log(\sigma_{ds(o)}) = \alpha_1 + \pi_1 W_{ds} + \zeta_1 dist_{ds} + \phi_{od} + \phi_{os} + \phi_{dK(s)} + \xi_{ods} \tag{20}$$

where $o \neq d$.[54] We use the residuals from this first stage, $\widehat{\xi}_{ods}$, as an additional regressor in our gravity equation estimated via PPML:

$$P_{ods} = \exp(\widetilde{\beta}^{Leave} \log(\sigma_{ds(o)}) + \zeta_2 dist_{ds} + \tau_2 \widehat{\xi}_{ods} + \phi_{od} + \phi_{os} + \phi_{dK(s)})\varepsilon_{ods} \tag{21}$$

[53]We have added a subscript o to denote that we take the average destination network size across years of displacement within an origin-school pair. We also defined network size this way in our baseline directed migration analysis in 3.3, but did not include an o subscript to avoid superfluous notation.

[54]Although the dependent variable in the first stage is in logs, the first stage is still linear and estimated via OLS. Thus we avoid the "forbidden regression" in Angrist and Pischke (2009).

The estimated $\widetilde{\beta}^{Leave}$ from Equation 21 is the 2SRI estimate. Compared to our baseline gravity equation of directed migration, the only difference is that we include $dist_{ds}$ as a regressor and the estimated first stage residual $\widehat{\xi}_{ods}$. Following our model's nested logit structure, we use these estimated parameters from Equation 21 to construct the inclusive value of the *Leave* nest, which we first defined in Equation 7a. Denoting this estimated inclusive value as $\widehat{IV}_{os}$, which includes the estimated first stage residual, we can now obtain a 2SRI estimate of β^{Stay}. We specify a linear first stage using the origin-specific instrument W_{os}:

$$\log(\sigma_{ose_i}) = \alpha_3 + \pi_3 W_{os} + \zeta_3 dist_{os} + \bar{X}'_{ose_i}\eta_3 + \phi_{oK(s)} + \delta_{e_i} + \lambda_3 \widehat{IV}_{os} + \xi_{ose_i} \tag{22}$$

where $\log(\sigma_{ose_i})$, the log number of co-alumni from school s in origin o in year e_i, is our potentially endogenous regressor. We include the same set of fixed effects as in our baseline out-mobility analysis. We collapse the individual controls included in our baseline out-mobility analysis to the same level as $\log(\sigma_{ose_i})$, which we denote as $\bar{X}'_{ose_i}$.[55] We estimate the first stage equation via OLS at the origin $\times$ school $\times$ year level, weighting observations by the number of individuals in each cell. We use the estimated first stage residual, $\widehat{\xi}_{ose_i}$, as an additional regressor in our binary logit from Equation 9, which modeled a job seeker's decision to stay or leave. We also include $dist_{os}$ as a regressor. We obtain our 2SRI estimate of β^{Stay} by re-estimating our binary logit:

$$\begin{aligned}\log\left(\frac{Pr(stay_i)}{1 - Pr(stay_i)}\right) = \alpha_4 + \beta^{Stay}\log(\sigma_{ose_i}) + \zeta_4 dist_{os} + \tau_4 \widehat{\xi}_{ose_i} \\ + X'_i\eta_4 + \phi_{oK(s)} + \delta_{e_i} - \lambda_4 \widehat{IV}_{os} + \epsilon_{ios}\end{aligned} \tag{23}$$

Because we estimate both β^{Stay} and $\widetilde{\beta}^{Leave}$ in multiple steps, we bootstrap standard errors (cluster re-sampling at the origin-school level, with 400 repetitions).

D.2 Multinomial Logit Model of Location Choice

Here, we consider a multinomial logit alternative to our nested logit model of location choice. Rather than first choose whether to stay or leave, and choose among non-origin cities conditional on leaving, we allow job seekers to choose among all cities in one step. This modification simply requires enforcing λ, the GEV parameter, to be equal to 1. We can then estimate a single β that governs both the stay vs. leave decision and directed choice over all cities. Accordingly, we re-estimate Equation 10 but on both movers and stayers, not

[55] We avoid estimating the first stage equation at the individual level and including non-averaged individual controls, since these controls affect the first stage residual yet our potentially endogenous regressor does not vary across individuals within the same origin $\times$ school $\times$ year cell.

just movers, thus allowing for $d = o$.

Under the multinomial logit structure, yet another approach to estimate a single β would be to adapt Moretti and Wilson (2017). Given our expression in Equation 8b for the choice probability of some destination city d, we can express, for job seekers who graduated from school s and are displaced in origin city o, the relative likelihood of choosing d over staying in o as a log-odds ratio that is linear in the difference between utility levels in the two cities:

$$\begin{aligned}\log(\frac{P_{ods}}{P_{oos}}) &= \beta[\log(\sigma_{ds}) - \log(\sigma_{os})] + (A_{ds} - A_{os}) + (B_d^{City} - B_o^{City}) - (r_d - r_o) \\ &\quad + (Z_{ds} - Z_{os}) - \widetilde{C}_{od}\end{aligned} \tag{24}$$

where P_{ods} is the number of job-seeking alumni from school s who are displaced in a mass layoff or firm closure in city o and move to city d 1-year post-displacement, and P_{oos} is the number of job-seeking alumni from school s who are displaced in city o but stay in o. We can absorb destination-origin differences in all of the utility components outside of network size with fixed effects, and obtain the following estimating equation, estimated via OLS:

$$\log(\frac{P_{ods}}{P_{oos}}) = \beta[\log(\sigma_{ds}) - \log(\sigma_{os})] + \phi_{od} + \phi_{ds} + \varepsilon_{ods} \tag{25}$$

Here, we include a set of origin metro $\times$ destination metro fixed effects ϕ_{od}, which absorbs differences in citywide amenities $B_d^{City} - B_o^{City}$; and differences in cost of living $r_d - r_o$. Furthermore, ϕ_{od} captures the moving cost from o to d, $\widetilde{C}_{od}$. We can directly absorb Z_{ds}, which captures correlated preferences for a potential destination metro among alumni of the same school, as well as A_{ds}, which captures city-school productivity matches across all destinations, by including destination metro $\times$ school fixed effects ϕ_{ds}. We cannot also include origin metro $\times$ school fixed effects and identify β. We could include origin $\times$ school strata fixed effects by invoking our identifying assumptions that $Z_{os} = Z_{oK(s)}$ and an additional assumption that A_{os} can be decomposed into some combination of $A_{oK(s)}$ plus additively separable city-specific and school-specific work utility components, for all schools within a sufficiently narrowly defined strata K. However, in practice, since estimation requires non-zero flows of both movers and stayers for a given origin $\times$ destination $\times$ school and origin $\times$ school cell, respectively, we are constrained by the number of non-zero flows in our sample of job seekers. Thus we decide to prioritize including destination $\times$ school fixed effects, which more directly addresses any immediate, potentially lingering identification concerns.

D.3 Incorporation of Same-Industry Networks into our Model of Location Choice

In Section 6.2, we extend our model of location choice, specifically by allowing the work utility in a location to depend on the number of co-alumni in a given city who work in the same industry from which a job seeker is displaced. This extension allows us to quantify the impact of same-industry local alumni network size on location choice.

With no adjustments to work utility y_{ds}, we can now identify β^{Stay} and $\widetilde{\beta}^{Leave}$ separately from the fixed city-school component of work utility A_{ds}. We estimate these parameters from our baseline model in both Equation 13, our binary logit relating the probability of staying to the same-industry network size, and a simpler version of Equation 14, our gravity equation of destination choice conditional on moving.

We also consider a more complex adjustment to the determination of a job seeker's work utility in a local labor market in Equation 4 to more flexibly allow for productivity matches between cities, industries and schools. For a worker from school s who is displaced from industry j, suppose the work utility for some job h in city d, y_{dsjh}, is additively separable into a school $\times$ industry component and city $\times$ industry component for the industry from which the job seeker was displaced, as well as a possible city $\times$ school component. The industry-specific terms capture the value of industry-specific human capital, while the city $\times$ school term provides more flexibility in allowing for both city and school to impact work utility. As in Equation 3, there is also an idiosyncratic match component ν_h that is i.i.d. with CDF $F(\nu_h)$. Thus our expression for the wage of job h is:

$$y_{dsjh} = \mu_{dj} + \mu_{sj} + \mu_{ds} + \nu_h \tag{26}$$

We note that job h does not necessarily have to be in the same industry of displacement j. Thus the industry-specific human capital that is tied to j has a broad impact on earnings, and we do not model potential cross-industry productivity matches, which would require a model of both location and industry choice that is beyond the scope of this paper.

Next, as in our baseline model, we assume that a job seeker has a finite number of job draws in each potential destination d. However, to account for the role of industry-specific human capital accrued in industry j, we now assume that this number is proportional to the number of co-alumni from school s working in j in that city, σ_{dsj}, by a factor of $a < 1$. As before, this assumption does not require that all draws come entirely from jobs where same-industry co-alumni are present, and instead simply reflects the idea that job seekers are more likely to sample more jobs in a city with many co-alumni working in the same industry from which they were just displaced and had accrued more industry-specific human capital. If we continue to assume that $F(\nu_h)$ is Type-1 Extreme Value (McFadden 1978) with scale parameter ω^{Leave}, then the expected value of the highest work utility job y_{dsjh} in a sample of $a\sigma_{dsj}$ draws, which we denote as y_{dsj}, is:

$$y_{dsj} = \mu_{dj} + \mu_{sj} + \mu_{ds} + \omega^{Leave}\gamma + \omega^{Leave}\log(a\sigma_{dsj}) \tag{27a}$$

$$\equiv A_{dj} + A_{sj} + A_{ds} + \omega^{Leave}\log(\sigma_{dsj}) \tag{27b}$$

where A_{dj}, A_{sj}, and A_{ds} capture the various match-specific components of work utility between cities, industries, and schools. The rest of our model from Section 3.1 remains unchanged. As such, in our directed mobility analysis in Section 6.2, our inclusion of destination $\times$ industry, origin $\times$ school $\times$ industry, and destination $\times$ school fixed effects, absorbs the aforementioned matches. Furthermore, destination $\times$ school fixed effects absorb both the impact of total co-alumni network size (which enters on the amenities side) and correlated location preferences within schools Z_{ds}. Thus our estimating equations in Section 6.2 are theoretically consistent with the model of location choice presented here, extended to incorporate industry-specific human capital.