Vertical Connections Matter: School Alumni Networks and Labor-Market Outcomes

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Abstract

This paper uses LinkedIn public profile data to investigate the influence of vertical connections (i.e., the relationships between senior and junior workers who are connected only through sharing the same alma mater) on labor-market outcomes. Specifically, I rely on an event-study design and an exposure framework to examine the extent to which vertical connections affect hirings and promotions, respectively. Taking the law sector as a case study, I find that having a senior worker who shares the same alma mater as a junior worker not only increases the junior worker's chances to be hired by the firm, especially at small-size firms, but also makes the junior worker more likely to be internally promoted. Investigations into the mechanisms suggest that the homophily channel may be at play for both hiring and promotions, but the information channel (i.e., learning about the ability/skills of the alumni from a given school) appears more important for promotions.

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1 Introduction

Nowadays, networking is crucial for one's professional career, notably to get an employment offer and/or to climb the job ladder. According to a recent LinkedIn study that surveyed nearly 16,000 LinkedIn members across 17 countries, 80% of workers consider networking as very important for their career success, and 70% of professionals hired in 2016 had a connection at their company (LinkedIn, 2017).

While the literature has documented the influence of close connections on labor-market outcomes (see Section 2 for a literature review), less is known about the role of "weak-tie relationships," which are characterized by infrequent or even sometimes absent interactions. It is indeed easier to think about why our family members, close friends, or coworkers ("strong ties") would want to help us succeed in life, by helping us find a job for example. However, it is more difficult to understand why someone that we barely know and may have never interacted with before would want to do the same. And yet, quite paradoxically, when it comes to finding a job at least, most individuals end up working where their weak ties work, as it has been documented across more than 50 countries (Gee, Jones, Fariss, Burke, and Fowler, 2017). Of our interest are the weak ties formed by the vertical connections through one's school alumni network. In what follows, these "vertical connections" refer to individuals who graduated from the same (higher-education) school but did not overlap while attending their school. They are "vertical" in the sense that they represent relationships of individuals who are unlikely to have interacted before.

In this paper, I investigate the extent to which vertical connections within school alumni networks matter for job placement and promotion. In particular, I seek to answer the following questions: *(i)* Are junior workers more likely to work at a firm when there is a senior worker from their alma mater who is already working there? *(ii)* Conditional on working at a given firm, are "(vertically) connected workers" more likely to get internally promoted then "non-connected workers" (i.e., workers who do not have a senior alum in the company)?

I identify three non-mutually exclusive channels through which vertical connections can potentially influence hiring and promotion on the labor market. I here focus on cases where a senior worker considers hiring or promoting a junior worker who graduated from the same school as them. For hiring, a senior worker may want to hire an alum junior worker because of their knowledge about the training that they received while in school, as they themselves went through a similar training, which they thought was pretty good (*human capital* story). In addition, a senior may want to hire an alum junior simply because they want to help the alumni from their school, regardless of how good their school training was (*homophily* story). Finally, the hiring may happen because the other partners at the firm have recently promoted to partner an associate from a school they had little information about, so they have now learned about the ability of the associates from that school and updated their beliefs accordingly, which makes them more willing to hire other associates who graduated from that same school (*information* story). For promotion, only the *homophily* and *information* channels seem to be relevant, albeit the reasoning behind the latter is slightly different – i.e., if the first partner from a typically less-prestigious school continues to do a good job, then the other partners at the firm update their beliefs about the ability of the associates from that school to be a competent partner, and they are thus more willing to promote them.

I take the law sector as a case study to attempt to empirically answer these questions and dig into the mechanisms. In this context, junior workers are junior lawyers/attorneys, also called "associates," whereas senior workers refer to "partners."[1] The law sector exhibits three features that makes it particularly appealing to study. First, networking is known for being crucial in that sector, as emphasized by the American Bar Association and law schools themselves ("[networking] is an important part of the legal profession and something that all attorneys, whether they like it or not, must do as part of their careers" (Stanford Law School, 2023)). Second, it is a profession where the school one graduated from matters a lot, in part due to the highly competitive labor market for attorneys, but also because law firms themselves are competing to attract client and employing attorneys who graduated from renowned law schools helps them distinguish themselves from competitors, through both their influential personal connections who may seeking legal representation and/or the prestige associated with their school (U.S. News, 2018). Third, the law profession has a well-defined job ladder (see Section 3 for more detail).

I further restrict my attention to attorneys working at Limited Liability Partnership [LLP] law firms in the New York-New Jersey-Pennsylvania [NY-NJ-PA] metropolitan area. I choose that geographical area because of its high concentration of lawyers – e.g., in 2020, one-fifth of all lawyers in the U.S. were in New York (14%), Pennsylvania (4%), and New Jersey (3%). In addition to having the highest number of lawyers, New York is also the state with the highest density of lawyers, with 9.3 lawyers per 1,000 residents, compared with a national average of 4 lawyers per 1,000 residents (American Bar Association, 2022).

I use data from a snapshot from May 2022 of LinkedIn public profiles for users who have ever worked in the NY-NJ-PA metropolitan area, which I obtained from RevelioLabs, a

[1] In this paper, I will loosely use "lawyers" and "attorneys" interchangeably. However, formally, all attorneys are lawyers, but not all the lawyers are attorneys. Furthermore, while both lawyers and attorneys have graduated from law school, only attorneys have passed the bar exam and have a license to practice law.

workforce intelligence company. This dataset allows me to reconstruct individuals' education and work history and to recover the school alumni and company networks, provided that users have accurately filled out their profile (see Section 5.2 for a discussion of the potential limitations of such data). My analysis samples restrict the data to jobs in LLP law firms and job roles categorized in the legal sector for individuals who obtained their law degree from 2000 onwards (see Section 5.3 for details on the data cleaning and sample restrictions).

With these data and context, I first investigate whether vertical connections in the context of school alumni networks matter for job placements. To do so, I implement an event-study design around the first observed alum partner. I find that the arrival of the first alum partner leads to an increase in the number and/or share of junior (i.e., non-partner) lawyers from the same school in the firm. This increase suggests that alum partners influence hiring decisions in favor of lawyers who share the same alma mater and/or they are somehow helping to retain them longer in the firm. The effect is more visible in smaller-size firms (where the influence of a given partner is greater) and for smaller-network schools (where networks are presumably more helpful because the schools tend to be less well-known) and larger-network schools (which are also typically more prestigious, so it is easier for them to place). For these effects to be causal, it is required that there are no shocks that systematically coincide with the arrival of the first alum partner. While I am unable to fully disentangle all the mechanisms behind the observed effects, some placebo analysis indicates that hiring decisions are not systematically made based upon a school's ranking and/or reputation and that the decision to hire graduates who share the same alma mater reflects preferences for such alumni.

I next examine whether alum partners increase an associate's chances of getting promoted to the rank of partner. In particular, I consider the spells of non-partner lawyers that are at least seven years out of law school, and I test whether (i) having an alum partner in the firm when an associate's spell ends and (ii) overlapping with any alum partner help the associate get subsequently promoted to partner at the firm, after controlling for various individual-, firm-, and school-level characteristics, as well as time effects. I find that the presence of an alum partner the year when an associate's spell ends does increase the chances of getting subsequently internally promoted, and so does overlapping with any alum partners but to a much smaller extent. However, this effect is considerably attenuated for the spells associated with firm-school pairs that already had an alum partner before the spell start whereas it is still large for the spells involving firm-school pairs that already had an alum partner before the spell start. Assuming that the set of controls accounts for all the factors that influence the probability of promoted through the exposure to an alum partner si that these effects are causal, these findings indicate that the information channel is more important than the homophily channel to explain the results.

The remainder of this paper is organized as follows. Section 2 details the contributions of this paper to the literature. Section 3 provides an overview of the institutional background of the law sector. Section 4 explains the conceptual framework that underlies the analyses to help think about potential mechanisms. Section 5 presents the data used to conduct the empirical analyses. Section 6 lays out the empirical methods. Section 7 presents and discusses the results of the analyses. Section 8 concludes.

2 Contributions and Related Literature

The contribution of this paper to the literature is twofold. First and foremost, it contributes to the strand of literature that examines the role of various types of social networks in labor markets (e.g., in terms of hiring, wage, retention, promotion, and job mobility). A few past studies have investigated the role of *neighbor* connections and found that there is a higher concentration of coworkers in the same city block (Bayer, Ross, and Topa, 2008) and census tracts (Hellerstein, McInerney, and Neumark, 2011), and that individuals living in neighborhoods that provide higher-quality employment networks tend to move to higher-paying firms (Schmutte, 2015).

Some other studies have emphasized the role of *coworker* connections and shown that they lead to the hiring of better-quality workers (Hensvik and Skans, 2016), greater job-to-job mobility and wage growth (Caldwell and Harmon, 2019), and higher chances of being appointed to a board of directors (von Essen and Smith, 2023). In a large-scale online randomized experiment, Rajkumar, Saint-Jacques, Bojinov, Brynjolfsson, and Aral (2022) randomly assigned LinkedIn members to receive new connection recommendations and found that these members ended up having more job mobility. In the field of political discrimination at work, Colonnelli, Neto, and Teso (2022) reveal how *copartisan workers* tend to be paid more and promoted at a faster rate.

Several papers have shown that *parental and friendship* connections increase the probability of getting hired (Corak and Piraino, 2011; Kramarz and Skans, 2014; Plug, van der Klaauw, and Ziegler, 2018; Staiger, 2021; San, 2022), landing in a higher-paid job in some cases (Pellizzari, 2010), and staying longer in the firm (Özer and Perc, 2021). A couple of other studies document how *social networks* in general help finding better-fit jobs in terms of non-pecuniary characteristics (Franzen and Hangartner, 2006) and *referrals* increase the likelihood of being hired (Pallais and Sands, 2016) as well as wages and job duration (Brown, Setren, and Topa, 2016; Dustmann, Glitz, Schönberg, and Brücker, 2016).

More closely related to my project is the thin literature on former *school peer* connections. Rider and Tan (2015) exploit the dissolutions of six large law firms as a quasi-experiment and finds that lawyers at these firms are more likely to join law firms with more former law school classmates following the dissolution. In a different context, two papers leverage the random assignment of students at Harvard. Shue (2013) takes advantage of the random assignment of Harvard MBA students to section-mates and finds that individuals who were randomly grouped together have more similar executive compensative. Similarly, Michelman, Price, and Zimmerman (2022) exploit the random assignment of male college students to dorm rooms and find that students from private schools exposed to peers who belong to exclusive college clubs are themselves more likely to *(i)* have a college and adult social membership, *(ii)* choose finance careers, and *(iii)* earn more.

My project departs from these papers and adds to the literature in two ways. First, instead of looking at *direct peer* connections, I study *vertical connections*, which are weaker social ties (i.e., the relationship between senior and junior workers), where a junior worker and a senior worker are connected only through their alma mater. Indeed, since they did not even overlap during their university years, they presumably did not have any prior social interactions. Second, although these three closely related papers use pretty neat sources of variation, they are quite restrictive in terms of sample representativeness and thus external validity. The first paper only looks at lawyers from a few large law firms, whereas I am able to include smaller-size law firms. The two other papers study Harvard alumni exclusively, which represent only the very top of the socio-economic distribution. By contrast, my sample of schools is much broader.

Second, this paper also adds to the vast literature on school/college value-added in labor markets. Many studies focus on selectivity, school inputs and resources as measures of school/college quality that affect various labor-market outcomes, such as earnings or employment – see Hanushek (2020) and Mountjoy and Hickman (2021) for recent reviews. However, these studies only examine factors that are easily and directly measurable. By contrast, this paper suggests that another value-add of a given school is the professional network it gives access to, via its alumni.

3 Institutional Background: Law Sector

This section provides an overview of the law profession under study; it does not intend to be comprehensive but instead it gives enough information to understand the context.

Individuals who want to become a lawyer typically attend law school and earn a juris doctor (JD) degree. The law school from which they graduate can matter a lot for lawyers' professional career.[2] For example, attending a U.S. News & World Report Top 14 ("T-14") law school has a strong signaling value, offers a strong professional network, and leads to better labor-market outcomes (Naven and Whalen, 2022).[3] Many of the graduates of the "T-14 law schools" go on to work for prestigious law firms, hold high-level positions in government, or serve as executives for Fortune 500 corporations.

The law profession has a well-defined job ladder with a pyramidal structure. The recruiting process for lawyers start while individuals are still in their law school program, which typically lasts three years. Law firms organize summer recruiting events on school campuses. They start recruiting summer associates (also called "summer clerks") during the summer after the first year. Law students who are hired then work as a summer associate in the summer following their second year, and if they did well (and the large majority of them do), they end up receiving a return offer. After graduating from law school, lawyers typically work as associate attorneys at law firms. Most lawyers first join as junior associates and after a few years become senior associates.[4] Later, successful senior associates get promoted to partners (they "make partner").

There exist different law firm partnership models (Clio, 2023). The traditional one follows a "single-tier approach" where senior lawyers get internally promoted to equity partners (with a share of the profits) after a certain number of years. This promotion is associated with a gain of power within the firm – e.g., they participate directly in decision making. In another partnership model, the "two-tier partnership," there are equity and non-equity partners. The latter often continue to receive a salary as their compensation, as they do not have an ownership stake in the firm. But, depending on the firm, they may also enjoy some voting rights. In medium- and larger-sized law firms, the partnership model might include senior and/or managing partners, where senior partners report to the managing partner, who is responsible for the overall management of the firm, including its day-to-day operations, profitability, business plans, and supervision of the partner selection process.

Not all associates eventually succeed in making partner. In fact, the attrition rate in 2021 was as high as 26% on average across 125 U.S. and Canadian law firms (NALP Foundation, 2022), and rose to 34% for associates of color. An attrition rate of 26% means that if a law firm starts with an associate class of 100 new junior associate hires, then a

[2]There are over 200 law schools in the United States that are accredited by the American Bar Association.

[3]Even though a few top schools have recently withdrawn from the U.S. News Ranking of law schools, law firms presumably continue to use a pre-withdrawal version of the ranking.

[4]Not all law firms make a clear distinction between the two positions, and if the position of senior associates exists in the firm, the exact number of years required to be promoted can vary from one law firm to another. These aspects both depend on the size and structure of the law firm.

decade later, only five of them are likely to remain at the firm. Associates who do not expect to make partner in their current firm have different options: they may (i) laterally move to a typically less-prestigious, smaller law firm before making partner (typically a few years prior to being up for partner, so that it does not appear they failed to make partner at their initial firm); (ii) go in-house to clients of their law firm; (iii) stay in their current firm and be given the title of "counsel" or "senior lawyer", with the understanding that they will unlikely be promoted to partners; (iv) forego the private sector in favor of jobs in government, non-profit institutes or academia; (v) start their own law firm; or (vi) simply drop out of the profession.[5]

4 Conceptual Framework

This section presents a conceptual framework to help think about the different (non-mutually exclusive) channels through which school alumni networks can affect labor market outcomes (i.e., hiring and promotion). In what follows, I describe these channels by focusing on the reasons why partners would want to hire non-partner lawyers of their alma mater (unless otherwise specified).[6] The goal here is to explain why school alumni networks, as opposed to performance or seniority, matter for job placements and promotions.

4.1 How School Alumni Networks Influence *Hiring* Decisions

School alumni networks can play an important role in hiring decisions through three main channels: homophily, information, and human capital. While these channels are non-mutually exclusive, I will describe them below in isolation of one another to have a clear description for each of them.

The *homophily* channel refers to a situation where a lawyer who graduated from a given law school gets hired by the partners who graduated from that same school as the latter want to help the former, precisely because they share the same alma mater. That vertical connection through attending the same school (albeit at different points in time) is the reason why the alum is hired.

The *human capital* channel describes the case where partners hire lawyers from their alma mater because they think/know that the training they receive while in law school is very good, as they have themselves gone through it. It may be especially true for

[5]Most associates wait to have been practicing for at least three years before joining the lateral market.

[6]I here restrict my attention to the law sector, but a similar reasoning can be applied to sector with a similar hierarchical and pyramidal job ladder.

schools that specialize in certain fields of law, so that when an associate makes partner, they may want to hire more junior associates who are more knowledgeable about these topics (through the training they received at their law school).

The *information* channel characterizes a situation where an associate is the first alum from their school to make partner at a firm and the partners at that firm have now updated their beliefs about the ability of the associates from that school, so they are more willing to hire junior attorneys from that same school again. The information story is presumably more prevalent for less-prestigious and smaller-network schools.

More generally, the smaller the firm is, the more power does an individual partner have (since there are fewer of them) over hiring and promotion decisions. In addition, the smaller the network of a law school, the more important will it be to have an alum partner present in the firm to help associates from their alma matter get hired and perhaps subsequently promoted.

4.2 How School Alumni Networks Influence *Promotion* Decisions

School alumni networks can also matter for (internal) promotion decisions within a law firm, either through the homophily channel or the information channel. In the *homophily* story, an associate gets promoted to partner only thanks to the help of the partner(s) of the same alma mater in the firm. By contrast, in the *information* story, an associate is the second alum to make partner in the firm because the other partners realized that the promotion of the first alum was a good decision, so they update their beliefs about alumni from that school being able to hold a partner position.

The *human capital* story is less relevant here because we are considering internal promotions only (as opposed to promotions from a lateral move), so the law school training per se is no longer relevant after a few years in the firm, where partners have observed the performance and skills of the associates when deciding whether or not to promote them.

5 Data

5.1 Source and Content

This paper uses a snapshot from May 2022 of all LinkedIn public profiles for users who have ever worked in the NY-NJ-PA metropolitan area. The data, which have been pre-cleaned and delivered by workforce intelligence company Revelio Labs, allow me all school alumni networks and law firm networks, provided that users have accurately filled out their profile. The data contains the employment history (job title, company name, start/end dates) and the education history (school name, degree, start/end dates) of users who have provided the information, as well as proxies for gender and race.[7]

5.2 Potential Limitations

One might be concerned about sample selection in the data. I argue that it is less worrisome in the context I am studying.

First, while not everyone is on LinkedIn, this paper focuses on college-educated workers, who typically do have a LinkedIn profile. In fact, about half (51%) of U.S. adults who have a Bachelor's or advanced degree report using LinkedIn in 2021, compared with 28% for individuals with some college and 10% for those who have at most a high school diploma (Pew Research Center, 2021).

Second, even though the data contain information from users whose profile is public, the default setting is "public." The amount of information displayed is customizable and whatever information that is made "public" is "visible to people who are not members, viewers who are not signed in to LinkedIn, or those who have not linked their LinkedIn account to their account on other approved services, subject to [the user's] off-LinkedIn visibility settings" (LinkedIn, 2023).

Third, although users may choose not to report all of their educational background and work history, conditional on being on LinkedIn, lawyers are presumably less likely to do so. I additionally report below some statistics showing that the key information is present.

5.3 Data Cleaning and Sample Restrictions

Even though the raw data delivered by Revelio Labs have been pre-cleaned, there are still some harmonizations and sample restrictions to be done. The standardization/harmonization is required for school and firm names, because only recently did LinkedIn include a drop-down menu that allows users to choose an existing company name; before that implementation, users had to manually enter their company name, which is more prone to typos and different naming conventions. For example, the data show that "Fordham University"

[7] These proxies are computed by Revelio Labs, using a proprietary algorithm. In particular, an individual's gender is predicted "using their first name by estimating the probabilities that the name is male or female. The model is informed by social security administration data. For example, if 70% of people named Lauren are female and 30% are male, our model will output a 0.7 probability that the person is female and 0.3 probability that the person is male. Similarly, [they] predict an individual's ethnicity using first name, last name, and location. The model draws from US census data for its predictions, in which it estimates the probability that a given individual belongs to a particular ethnic group from the set {White, Black, API (Asian and Pacific Islander), Hispanic, Multiple (Two or More Ethnicities), Native}" (Revelio Labs, 2023a).

is referred to with seven different spellings/names: "Fordham," "Fordham Law," "Fordham Law School," "Fordham School of Law," "Fordham University," "Fordham University School of Law," and "Forham University School of Law" (the typo in the last name is reported as such).

Out of the approximately 11 million job spells in the NY-NJ-PA MSA found in the raw data, I first select job roles that are categorized in the legal sector, which shrinks the sample to more than 355,000 spells. This categorization is based on an algorithm that uses job title, job description, individuals' skills and past experience (Revelio Labs, 2023b).

I further restrict the sample to spells that are associated with a *raw* company name that contains "LLP" (Limited Liability Partnership), which yields more than 93,000 spells.[8]

I then select job spells that (i) contains information on their start date (less than 0.5% of spells are dropped), (ii) started from year 2000 onwards (more than 90,000 spells), because older cohorts are less likely to be on LinkedIn, so sample selection is a more severe issue for older workers, and (iii) ever had more than three job spells (more than 88,000 spells), to exclude "solo practitioners" and firms whose networks of attorneys are not represented on LinkedIn.

5.4 Summary Statistics

With the aforementioned sample restrictions, we are left with about 88,000 spells, for which 23% do not have an end date. Appendix Figure A.1 displays the distribution of job spell duration, separately for job spells with and without end dates (the latter are replaced with May 2022, the month the snapshot was taken): the mean duration is 40 months and the median duration is 25 months. Three-quarters of these spells are lawyer jobs (i.e., the job title contains "associate," "attorney," "lawyer," "clerk," "counsel," "partner," "shareholder"), among which 13% are partner positions.

The sample of spells cover nearly 60,000 workers, with two-thirds of them reporting holding a JD and the average number of spells per worker being 1.5. After standardizing 2,008 raw company names and 527 school names, the sample yields 1,549 LLP law firms and 255 law schools. Note that these schools are restricted to law schools that had an alumnus with a JD who reported holding a senior lawyer position in an LLP firm. The mean (median) number of spells per firm is 57 (11) and the mean (median) number of spells per school is 245 (10).

Using the aforementioned sample of spells, one can provide suggestive evidence that

[8]Law firms typically choose an LLP (Limited Liability Partnership) business form over an LLC (Limited Liability Company) one (Forbes, 2022). Note that by applying such a restriction, which is useful to identify law firms, I am missing job spells for users who did not specify "LLP" in their firm name.

law school alumni are not randomly allocated across law firms. Appendix Figure A.2(a) displays a heat map that answers the following question: within a large law firm, what share of *lawyer* spells are occupied by the alumni of a large-network school? The shares are computed for the 20 law schools with the largest networks (per the number of observed spells in the data) at the 20 largest law firms (also per the number of observed spells in the data). It shows that larger law firms have a higher concentration of lawyers from the largest-network schools.

Appendix Figure A.1(b) reproduces a similar heat map but focusing on the share of *partners* instead. Here as well, large law firms tend to attract/promote partners who are from a few top schools. Note that the share of partners with the same alma mater can be as high as 42% (i.e., NYU alumni at Dechert). Both of these subfigures are computed from a single snapshot, so they do not capture any evolution over time.

Appendix Figure A.3 show times series of the number of observed spells at a given law firm over time, broken down by type of spells. At each of the large firm shown, the number of spells rises over time, with only a very few spells observed before 2005. This increase presumably reflects the fact that older cohorts of individuals are less likely to be on LinkedIn.

5.5 Analysis Samples

Since the data are less reliable for earlier periods of time, I make additional restrictions for my analysis samples. The analysis sample of interest depends on the outcome variable used (i.e., hires and promotions), which is itself associated with a specific identification strategy (see Section 6 for more detail).

To study hires, I construct a panel dataset at the firm-school-year level and restrict the sample to (i) individuals who obtained their J.D. from 2000 onwards, (ii) job spells with both law school and law firm names, and (ii) firm-school pairs whose first partner is observed between 2010 and 2017 in order to have a balanced panel.[9]

I also perform subsample analyses, broken down by the size of the law firms (as measured by the number of lawyers) and the size of the school networks (as measured by the number of alumni among the lawyers). The left panel of Figure 1 shows the distribution of firm sizes, based on the average yearly number of job spells: it is right skewed, with the majority of firms being "small." Firms with 15 or fewer lawyers are categorized as "small-size firms" (394 firms), those with 16-50 lawyers are categorized as "mid-size firms"

[9] I choose 2010 as a lower bound because the pre-2005 data do not seem reliable, and 2017 as the upper bound to ensure that there are at least 5 years of "post-treatment data" (where the "treatment" here is the first observed partner from a given school).

(94 firms), and those with more than 50 lawyers per year on average are categorized as "large-size firms" (41 firms). The right panel of Figure 1 shows the distribution of school network sizes, also based on the average yearly number of job spells: this distribution is also right-skewed but there is a also a peak of schools with more than 100 lawyer spells per year. I classify school network sizes as follows: "small-network schools" (103 schools) have 20 or fewer lawyers, "medium-network schools" (94 schools) have 21-50 lawyers, and "large-network schools" (34 schools) have more than 50 lawyers per year on average.

To study (internal) promotions, I construct a spell-level dataset that is restricted (i) post-graduation junior (i.e., non-partner) lawyer spells, (ii) lawyers who obtained their J.D. from 2000 onwards, (iii) job spells with both law school and law firm names, and (iv) lawyers who are more than six years out of law school.[10] That restriction yields 11k+ spells, which cover nearly 9k individuals (among whom 7k+ appear only once), 1k+ firms and almost 200 schools. The average spell length is 58 months (i.e., almost 5 years). Note that a spell here refers to a combination of a job title and company. For example, a worker who switched firms and is observed to have had one job title in each firm would be assigned to have two spells, and a worker who is observed to have had two different job titles within the same firm would also be assigned to have two spells.

6 Empirical Methods

I employ distinct identification strategies depending on the outcome variable of interest: (i) event studies around the first observed alum partner for hires, and (ii) exposure to/overlap with an alum partner for internal promotions.

6.1 Hires

To measure the effect of school alumni networks on hires, I implement an event-study analysis around the first observed alum partner for each pair of schools and firms. The idea is to examine what happens to the number of non-partner lawyers who graduated from a given school a few years before and after the first partner from that school is observed.

To get the intuition behind this idea, I plot the raw data for six combinations for schools-firms in Figure 2. If the arrival of an alum partner did not have any effect, then the

[10]The last restriction is necessary to avoid including junior lawyers who are not up yet for being promoted to partner. Note that I chose a cutoff of six years to be conservative. The minimum duration to be eligible for promotion actually vary from one law firm to another. At many firms, it takes 8, 9, 10 or 11 years to be eligible to make partner, and most firms start to review associates four to six years into their practice with respect to whether they are capable of making partner at the firm (FindLaw, 2016).

pre-arrival trend should be continued in the years following the arrival, as is visible for Columbia alumni at Milbank LLP (in the left-hand-side middle subfigure). On the contrary, a discontinuation in the pre-arrival trend following the arrival of the alum partner would suggest an effect. In particular, if anything, we typically observe an increase, as for the Stanford alumni at Davis Polk Wardwell LLP (right-hand-side top subfigure) for instance.

However, since there are more than 1,500 pairs of schools-firms in my main analysis sample, with the first partner alum being observed at different points in time, it would be very difficult to get an overall understanding of the effect by plotting that many figures. I therefore pool all of these "events" by showing their average effect in one figure, after normalizing to zero the time when we observe the first alum partner.

Formally, I estimate by OLS the following regression:

$$junior\_lawyers_{s,f,t} = \alpha + \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \beta_\tau \, \mathbb{1}\{t=\tau\} + \omega_s + \phi_f + \theta_t + \varepsilon_{s,f,t} \tag{1}$$

where $junior\_lawyers_{s,c,t}$ is either the "leave-one-out" number or the "leave-one-out" share of junior (i.e., non-partner) lawyers from school s at firm f in year t;[11] $\mathbb{1}\{t=\tau\}$ is a dummy variable that takes value one for the year in which the first alum partner is observed ($t=0$) and each of the five years before and after that year, other than the year that precedes it ($t=-1$); ω_s, ϕ_f, and θ_t denote school, firm, and time fixed effects, respectively; $\varepsilon_{s,f,t}$ is the error term.

With the school/firm fixed effects, I remove variation at the school/firm level that does not change over time, such as geographic location or reputation. With the year fixed effects, I remove shocks that are common to the entire U.S. economy in a given year.

The coefficients of interest here are the β_τ's – they capture the average of the outcome variable across pairs of schools and firms that observe their first alum partner τ years before (if τ is negative) or after (if τ is positive), controlling for common shocks and time-invariant school- and firm-level characteristics. The estimates are all relative to the year that precedes the arrival of the first alum partner (i.e., the "event"), which is the omitted category in the regression. Note that the use of pre- and post-event dummies enables me not to impose any particular functional forms on how the first alum partner may influence the number/share of non-partner lawyers from the same school in a given firm.

[11] "Leave-one-out" means excluding any junior lawyers who got internally promoted to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. To compute the "leave-one-out" share of junior lawyers, I divide the "leave-one-out" number of junior lawyers from school s at firm f in year t by the "leave-one-out" total number of junior lawyers at firm f in the same year, and I multiply by 100.

For this identification strategy to be valid for causal estimation, we need to assume that that there do not exist contemporaneous shocks that are timed with the observation of the first alum partner for each school-firm pair. In particular, one might worry that the number/share of junior alum lawyers *systematically* increases in a firm for reasons that are unrelated to the hire/promotion of the first alum partner. For example, if a law school decides to expand the size of its cohorts, it may have way more graduates on the market, which might coincidentally coincide with the hire/promotion of the first alum partner in a given firm.

Even though this type of threat to validity is unlikely to be a concern here given the large number of school-firm pairs, I perform a placebo analysis to alleviate such concerns. The placebo test consists in assigning a twin school to each school in the data (e.g., Harvard is assigned Yale as its twin school) and checking how the number/share of junior lawyers who graduated from that twin school (e.g., Yale) is affected by the hire/promotion of the first partner from the initial school (e.g., Harvard).

For the assignment of twin schools, I proceed as follows: First, I rank schools based on the yearly average number of lawyer spells in the data.[12] I then group them two by two to create the twins. For example, at the top, we assign Fordham University to be paired with New York University, and Brooklyn College with Columbia University. Once twins have been assigned, for each of the first alum partners that I observe in a given firm, I compute the number/share of junior lawyers from the corresponding twin school in the event window (i.e., five years before and after the first alum partner), which I then use as the outcome variable. To put it differently, I simply replace the dependent variable in equation (1) with the number/share of junior lawyers from the *twin* school instead of the *same* school as the first alum partner (which serves as the "event").

6.2 Internal Promotions ("Making Partner")

To study promotions, I adopt a different strategy, which focuses on exposure to an alum partner and uses the spell-level dataset described at the end of subsection 5.5. The idea here is to assess whether a junior (i.e., non-partner) lawyer is more likely to be subsequently internally promoted when there is an alum partner at the time when the promotion decision was made (i.e., presumably in the year that precedes the start of the partner

[12] Note that I could have used the U.S. News Ranking of law schools instead. I opted not to retain that ranking because it considers *all* the law schools in the U.S. whereas my analysis focuses on the North-East coast of the U.S., which tends to recruit more from the nearby law schools, for proximity reasons.

position).[13] I formalize this idea with the following regression, which I estimate by OLS:

$$\mathbb{1}\{promoted_{i(s),f,t}\} = \tilde{\alpha} + \gamma\ \mathbb{1}\{alum\_partner_{s,f,t}\} + \tilde{\omega}_s + \tilde{\phi}_f + \tilde{\theta}_t + \boldsymbol{X'}_{i(,t)}\Delta + \boldsymbol{S'}_{s,t}\Sigma + \boldsymbol{F'}_{f,t}\Omega + \eta_{i(s),f,t} \quad (2)$$

The dependent variable, $\mathbb{1}\{promoted_{i(s),f,t+1}\}$, is a dummy variable that is equal to one if junior lawyer i from school s who is working at firm f is internally promoted in year t, which corresponds to the end year of their job spell, and zero otherwise. The main regressor of interest, $\mathbb{1}\{alum\_partner_{s,f,t}\}$, is a dummy variable that is equal to one if there is a partner from the same alma mater (school s) who is present in the firm (f) the year before the junior's promotion is effective (t), and zero otherwise. I also try a version of that specification where the main regressor is the number of years an associate overlapped with an alum partner during their job spell. The idea here is to evaluate whether overlapping with an alum partner for a longer period increases the chances of getting promoted.

Like before, I include three sets of fixed effects, at the school ($\tilde{\omega}_s$), firm ($\tilde{\phi}_f$), and year ($\tilde{\theta}_t$) level. The school (firm) fixed effects capture any time-invariant school-level (firm-level) characteristics that influence the likelihood that an associate makes partner. For instance, a firm that is located in an area that for some reason has a high demand for partners is more likely to promote associate to partners. The year fixed effects capture any U.S. economy-wide shocks that would affect promotions in a similar way – e.g., a recession is likely to reduce the number of promotions.

In addition, I include a vector of individual-level characteristics ($\boldsymbol{X}_{i(,t)}$) that may or may not vary over time (i.e., gender, race, and years of experience), and time-variant school- ($\boldsymbol{S}_{s,t}$) and firm ($\boldsymbol{F}_{f,t}$)-level characteristics (i.e., the size of the firm as well as the size of the school network, in terms of associates and partners for both).[14] The latter would capture a growing school network that could affect the likelihood of being promoted. For example, we are more likely to observe associates who graduated from a school that has a larger network make partner simply because there are more of them.

For this specification to isolate a causal effect of the presence of/exposure to an alum partner, we would require that there exist no factors that are not accounted for by the

[13]Because I do not always observe the month in which the new partner role starts, I assume that the promotion decision is made the year before the new role starts. Promotion decisions are typically announced at the beginning of the new fiscal year, with the new role starting in January. Note also that I only look at *internal* promotions, as opposed to promotions following a lateral move, because I want to know whether exposure to a partner within the firm matters.

[14]Based on the predicted probabilities for gender and race that RevelioLabs provided, I assign an individual to be (i) female if their predicted probability for gender is greater than 0.5, and (ii) white/Hispanic/Black/Pacific Islander if their predicted probability for the corresponding racial/ethnic group is greater than 0.4. Note that the resulting binary variables that indicate an individual's racial/ethnic group are collectively exhaustive and mutually exclusive.

control variables (i.e., that are left in the error term, $\eta_{i(s),f,t}$) and that affect both the presence of an alum partner and the promotion of an associate. It may be difficult to think of any of such factors given all the controls that are already included, but one (far-fetched) story that would constitute a threat to causality is the following. A significant fraction of the associates who got promoted come from families of lawyers who are well-connected and happened to have helped the partners who share the same alma mater as the associates who got promoted, so the partners helped back the families by having their children make partner as well. At the same time, the family connections also helped the associates get promoted. Hence, the associates' family connections affected both their promotion and the presence of the alum partners.

7 Results: Vertical School Connections Help

In this section, I show and discuss the results from the analyses laid out above in the light of the mechanisms presented in Section 4. Note that I will not be able to disentangle all the potential mechanisms I have described in that section. I first present and discuss the results on hirings, then I proceed with the results and discussions on internal promotions.

7.1 Results on Hirings

From running Specification (1), one would expect that if vertical connections through one's law school matter, then there should not be any pre-trends in the years before the first observed alum partner (i.e., the coefficients for $t < -1$ should not be statistically significantly different from the one at $t = -1$), but the number/share of non-partner alum lawyers should be statistically positive from then on (i.e., for $t \geq 0$). The darker purple lines in Figure 3 confirm this hypothesis: both the specification in terms of *number* (panel (a)) and *share* (panel (b)) of non-partner alum lawyers suggest that when an associate is the first alum to be promoted or to join as a partner in their firm, they seem to influence the hiring decisions by favoring junior lawyers who share the same alma mater.

Perhaps quite surprisingly, the increase is visible from the year when the first alum partner is observed ($t = 0$): for example, the number (share) of non-partner alum lawyers increases by 18% (30%) from the year that precedes the arrival of the first alum partner (Figure 3, panels (c) and (d)). However, it is actually not completely unrealistic given that partners typically start their role at the beginning of the year while junior associates, especially when they had just passed the bar, tend to start in the fall.

One might suspect that (i) the influence that a given partner has on hiring decisions is greater at smaller law firms, that (ii) a partner who is from a less-prestigious school, which typically has a smaller network of alumni, is more willing to help junior lawyers from their own school, and that (iii) partners from more-prestigious schools, which typically have larger networks of alumni, would have a preference for junior lawyers who share the same alma mater, if only for the reputation of the school. To test these hypotheses, I split the analysis sample into subsamples that vary by the size of the school network and the size of the firm (both in terms of the average yearly number of lawyers observed in the data).

Focusing first on the subsamples by firm size (Figures 4-5-6), we find statistically significant effects only for the subsample of small-size firms (Figure 4), which confirms the first hypothesis. Note, however, that the positive effects found in the post-treatment period (i.e., for $t \geq 0$) using the share of junior alum lawyers (Figure 4, panel (b)) is not reflected in the number of junior lawyers (Figure 4, panel (a)). One possible explanation behind this apparent discrepancy is that, given the high attrition rate in the law sector, the alum partner helped retain associates from their alma mater, so that the number of alum associates would remain stable but the share would increase.

Focusing now on the subsamples by school-network size (Figures 7-8-9), our findings are consistent with the second and third hypotheses that the influence of partners is greater for alumni who are from small- and large-network schools. Indeed, for small- and large-network schools, we find that both the number and the share of non-partner alum lawyers increase after observing the first alum partner (Figures 7 and 9). For small-network schools, the magnitude of the increase appears large when expressed in percentage changes (Figure 7, panels (c) and (d)) but we are here looking at small-network schools, which are more likely to be represented at smaller-size firms.

While all of these findings could be consistent with the three channels described in Section 4, the current analyses do not enable us to disentangle the mechanisms at play. One can argue that the information channel, perhaps in combination with the homophily channel, is likely to be the main driver for alumni from smaller-network schools while the human capital channel, also potentially combined with the homophily channel, is more prevalent for alumni from more-prestigious schools.

In an attempt to rule out a human capital story where an associate is hired because of the prestige and/or the quality of the training associated with their law school, I conduct a placebo analysis where I use the same set of events as before (i.e., first observed alum partner) but I change the outcome variable to be the number/share of non-partner lawyers from their assigned "placebo school" (thereafter "twin school"), instead of the same school as the partner. I proceed as follows to assign "twin schools": I first rank all the schools that are present in my data based on the average yearly number of observed lawyers. Then I group them two by two, using the order of the ranking. Finally, for each school in the event-study analyses (described in Section 6.1), I compute the "leave-one-out" number/share of non-partner lawyers from their assigned twin school. This assignment serves as a proxy for the quality/prestige of the school, as two schools that are similarly ranked are somewhat equivalent in the eye of a recruiter. The alumni of these schools should therefore be equally likely to be hired.

One non-negligible caveat with this reasoning is that this assignment does not take into account any potential specialization of schools, so that it would not account for situations where recruiters prefer alumni from one school over their twin school only because the latter school is better-known for its training in a given law domain. Despite this limitation, I view the results of the placebo analysis as suggestive.

Appendix Figures A.4, A.5, and A.6 present the results for the placebo event studies using the whole sample, by firm size subsample, and by school-network size subsample, respectively. Quite reassuringly, we do not find any significant effect in any of these placebo event studies. In virtually all the placebo event-study plots, the estimates are statistically indistinguishable from the corresponding coefficients at $t = -1$ (which is the omitted category). The only two notable exceptions are for the number of non-partner lawyers at large-size firms (Appendix Figure A.5, panel (e)) and the share of non-partner lawyers from medium-network (twin) schools (Appendix Figure A.6, panel (d)): the former plot simply exhibits an upload-sloping trend over time whereas the latter a small and gradual but noisy increasing share but the confidence intervals are too wide to draw a firm conclusion.

All in all, the event-study plots suggest that vertical school connections are helpful to get hired at law firms. Lawyers who got promoted partners tend to influence hiring decisions in favor of recruits who share the same alma mater. These vertical connections appear to matter more in smaller-size firms, where decisions are made by only a few partners, and for small- and large-network schools. While the present analyses do not allow us to disentangle all the mechanisms at play, it appears that these alma-mater preferences are not explained by the ranking of schools, as we do not observe similar patterns for similarly-ranked (i.e., "twin") schools in the placebo analysis.

7.2 Results on Promotions

Now that we have established that vertical connections are useful for hiring, the natural next question is whether they are also helpful to get promoted (i.e., to "make partner"). To examine this question, I report the results of the analysis laid out in Section 6.2.

I begin by reporting the raw means (i.e., run the regression without any controls): Column (1) of Table 1 indicates that, on average, 3.2% of the associates who are at least seven years post graduation get subsequently internally promoted to partner when there is no alum partner in the company the year their spell ends, compared with 17% for when there is an alum partner (i.e., a more-than-fourfold difference in the chances of getting promoted). Because the association between the presence of an alum partner and the likelihood of getting internally promoted may be both influenced by other factors, I then sequentially add other sets of controls.

Once I add spell end year fixed effects and individual-level controls (which include gender, race, and years of experience since graduation), the coefficient on the main regressor of interest (namely, having an alum partner when the spell ended) is not affected. Having an alum partner when an associate's spell ends is still associated with a 0.14-point increase in the probability (or equivalently, a 14-percentage-point increase in the chances) of being subsequently internally promoted (see Column (2) of Table 1). Note that being a female associate negatively affects the chances of being promoted, while being nonwhite actually increases such chances. The latter result might be surprising in light of the high attrition rates and the anecdotal evidence that people of color face additional challenges in the law sector. However, remark that we are here only considering the "survivors," i.e., the associates who stayed in the law sector for at least seven years after graduating from law school. They constitute a selected sample, and presumably even more so for nonwhite associates. Unexpectedly, having more years of experience is positively associated with being promoted.

Replacing the individual-level controls with either firm-level controls (see Column (3) of Table 1) or school-level controls (see Column (4) of Table 1) does not alter the estimate of the main regressor of interest either. Quite unsurprisingly, the larger the firm is in terms of the number of lawyers, the more likely an associate is to get promoted, if only because there are more open partner spots; but the larger the firm is in terms of the number of partners, the less likely an associate is to get promoted, because the hiring decision power is shared across more partners and there may be fewer open partner positions available (see Column (3) of Table 1). Similarly, a larger school network in terms of the number of lawyers is associated with a higher probability of getting promoted (see Column (4) of Table 1). However, quite unexpectedly, if the school network is measured in terms of its number of partners, then the association with the probability of being promoted becomes negative. Note that the magnitudes of the coefficients on these firm- and school-level controls are all pretty small, and that we have not yet included all the controls together, which is what we do next.

Reassuringly, including all the individual-, firm-, and school-level controls barely affects the estimate on the main regressor of interest: the presence of an alum partner in the law firm when an associate ends their job spell increases by 15 percentage points (pp) the likelihood of that associate being subsequently promoted to partner in that firm. Consistent with the explanations provided previously, being more senior (in terms of years of experience) and being nonwhite increases the promotion chances whereas being a woman and working at a firm with a larger number of partners decrease the promotion chances. The size of the firm or the school network does not have any statistically detectable effect, except for the number of partners in the law firm, which here as well has a small negative effect on the promotion chances.

To disentangle the homophily channel from the information channel (see Section 4.2 for a reminder), since both could be at play behind these results, I break down the analysis sample into spells with firm-school pairs that never had an alum partner before the spell start and those that already had one before the spell start. This sample split allows me to control for the information that the partners at a firm may have historically acquired about the ability of the alumni from a given school to hold a partner position. Restricting the sample to firm-school pairs that already had an alum partner before the spell start can therefore be viewed as shutting down the information channel. In this case, finding an effect would suggest that there is some referrals story at play: even though the firm has already acquired information about the alumni of a given school, having an alum partner who is present when the promotion decision occurs still helps junior lawyers.

Tables 2 and 3 present the results for the sample of school-firm pairs that never had any alum partner before the spell start vs. those that did already have at least one, respectively. Comparing the first columns across the two tables indicates that the presence of an alum partner when the spell ends is associated with a 29-pp increase when there was no alum partner before the spell start, compared to a 6.5-pp increase when there was already at least one. This large difference suggests that the information channel plays an important role: after promoting the first partner from a given school, the firm seems to update its beliefs about the alumni from that school. The fact that the effect still persists for the sample of school-firm pairs that already had an alum partner before the spell start (i.e., where firms have already acquired information about the alumni of a given school), albeit it is of a smaller magnitude, suggests that there is still some homophily channel at work. Remarkably, these point estimates are barely affected by the inclusion of all the controls (see Columns (5) in Tables 2 and 3), which confirms that both channels are present, but the information one seems more important than the referrals one.

While it appears important to have an alum partner in the firm for an associate to make partner, one might wonder whether "being exposed to" an alum partner for a longer duration also increases an associate's promotion chances. Indeed, overlapping with an alum partner for a longer duration implies more opportunities to interact with them and potentially being mentored by them.

To test this hypothesis, I replace the main regressor of interest to be the number of years (as calculated by dividing the number of months by 12) of overlap with an alum partner. I find that being more "exposed" to an alum partner appears way less important to get promoted than having an alum partner in the firm when the promotion decision is made. Indeed, having an additional year of overlap with any alum partner increases an associate's likelihood of getting promoted by less than 1 pp (Column (6) of Table 4, from a baseline of 7% for associates who are promoted but did not overlap at all with any alum partners at their firm (Column (1) of Table 4). A back-of-the-envelope calculation suggests that it would require approximately 15 years of overlap to find a similar effect as having an alum partner in the firm when promotion decisions are made.

To assess the contribution of the referrals and information channels, I again split the analysis sample into one that contains only spells with company-school pairs that never had an alum partner before the spell start and another one that contains only spells with company-school pairs that already had an alum partner before the spell start. Tables 5 and 6 display the results. Here as well, overlapping with an alum partner seems to have a relatively bigger impact on promotion chances for spells involving firm-school pairs that never had any alum partner before the spell start: an additional year of overlap increases by 1.6 pp the likelihood of being subsequently internally promoted (Column (5) of 5), compared with 0.5 pp in the other subsample (Column (5) of 6). Here as well, the difference suggests that the homophily channel does exist but that the information channel may be more important.

Taken together, the findings indicate that vertical connections through one's alma mater help non only to get hired but also to subsequently make partner. It seems though that the effects are mostly driven by the information channel, rather than the homophily channel.

8 Concluding Remarks

In this paper, I study the extent to which vertical connections through one's school alumni networks affect one's labor-market outcomes. To that end, I take the law sector in the NY-NJ-PA metropolitan area as a case study and use public LinkedIn profile data to examine whether being connected to a senior worker (i.e., a partner in the context of the law sector) helps a junior worker (i.e., an associate in the context of the law sector) who shares the same alma mater to get a job at the (law) firm and to subsequently be internally promoted.

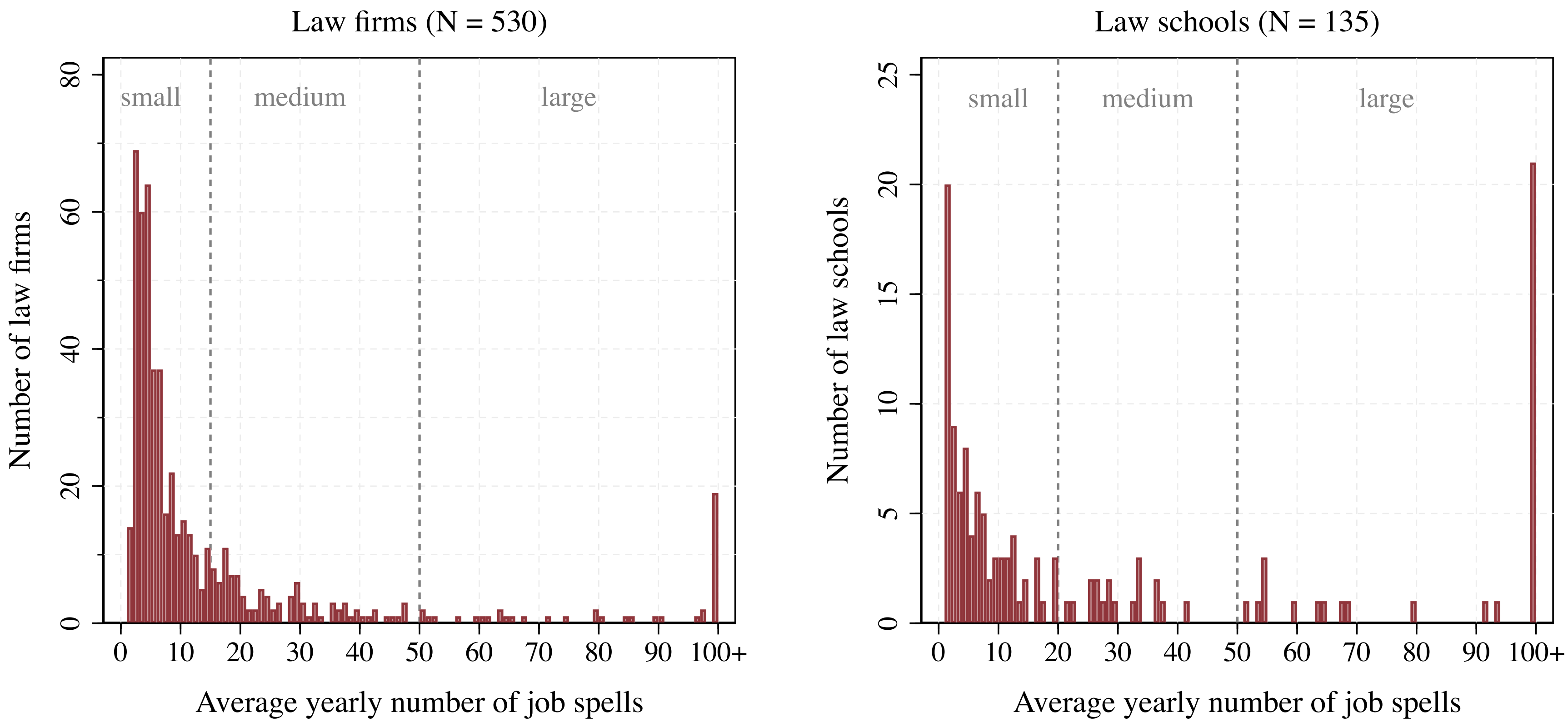
The results of my analyses suggest that it is helpful for junior workers (i.e., associates) to be connected via their via alma mater to senior workers (i.e., partners): not only do these vertical connections help them be hired by a (law) firm, but having such connections also makes them more likely to get promoted within the firm. Indeed, I find an increase in the number/share of junior alum workers (i.e., non-partner alum lawyers) following the first observed senior worker (i.e., partner) who shares the same alma mater as the junior workers. The effects are more pronounced (i) at smaller-size firms, where the influence of a worker is more important, (ii) for smaller-network schools, which tend to be less prestigious and well-known, and (iii) for larger-network schools, which tend to be more well-known. While my investigation into the mechanisms does not allow me to fully disentangle all the mechanisms at play, it appears that the decision to hire graduates from one's alma mater reflects to some extent pure preferences for these alumni (arguably due to homophily). As for promotions, I find that the presence of an alum senior worker (i.e., partner) increases an alum junior worker's likelihood of getting internally promoted to partner. While exposure to an alum senior also raises that likelihood, it appears way less helpful than having the partner present in the firm when promotion decisions are made. Here, the information channels seems more important than the homophily channel to explain these results.

The next steps of this research project involve conducting heterogeneity analyses by gender and race/ethnicity and finding an external data source to check the representativeness and accuracy of my data. Further research could also try to better isolate some of the mechanisms, for example, by collecting data on the domain specializations of law firms and law schools, and including the newly collected information in the analyses.

Even though I focus my attention on the legal sector, I argue that the findings are applicable more broadly to any professional sectors where hirings and promotions are influenced by school alumni networks. In particular, knowing whether gender and racial minorities are adversely affected by the absence of such networks has clear implications in terms of social policy regarding gender and racial inequalities. For example, if non-white senior alumni help diversify the profession by hiring and promoting more non-white juniors, then there may be a case for advocating for race-based affirmative action in universities. More broadly, there would be a case for promoting initiatives that attract racial and gender minorities to fields of study (e.g., STEM) and career paths that are predominantly white and/or male.

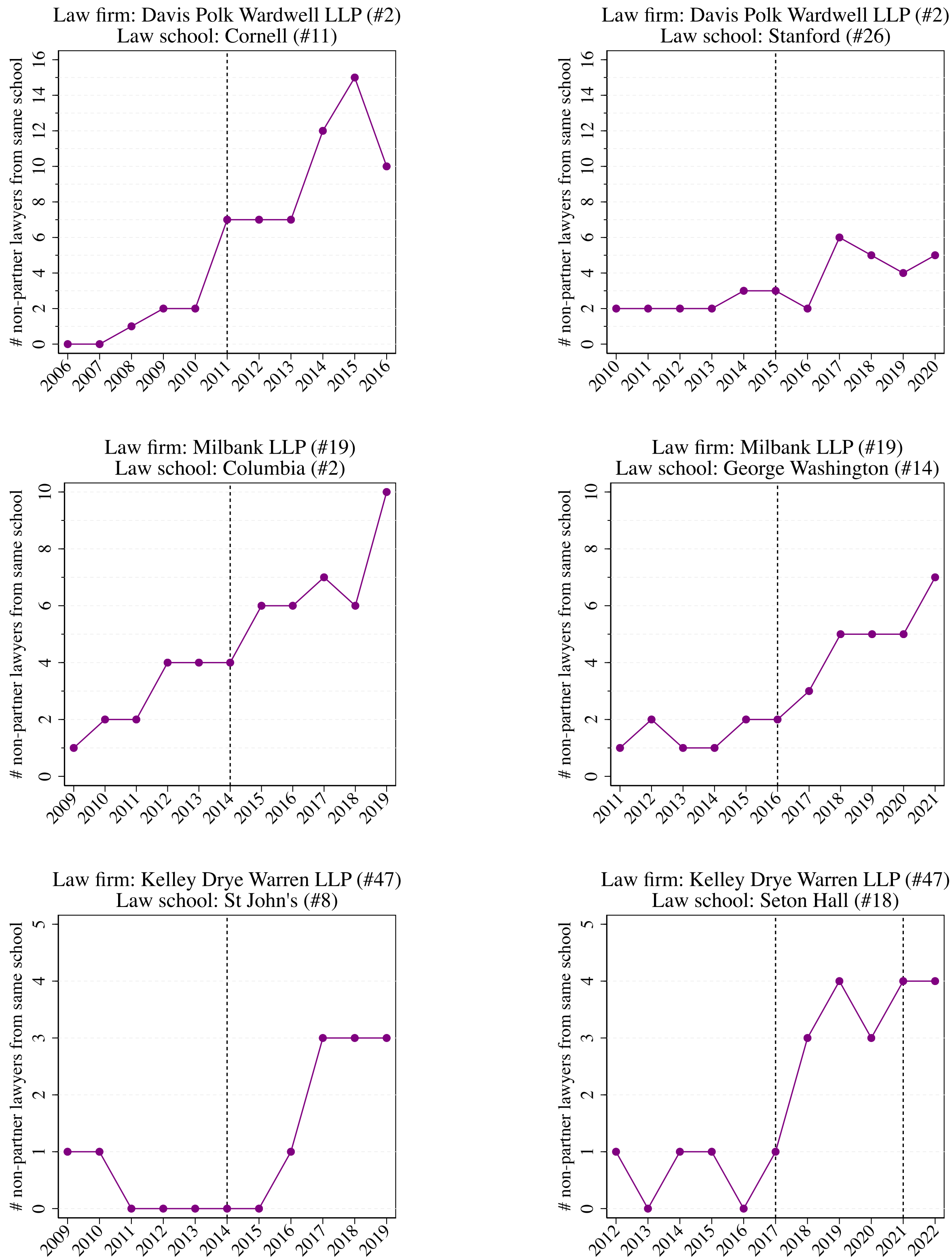
Main Figures and Tables

FIGURE 1: SUBSAMPLES OF FIRMS AND SCHOOLS WITH 100+ LAWYER SPELLS PER YEAR ON AVERAGE



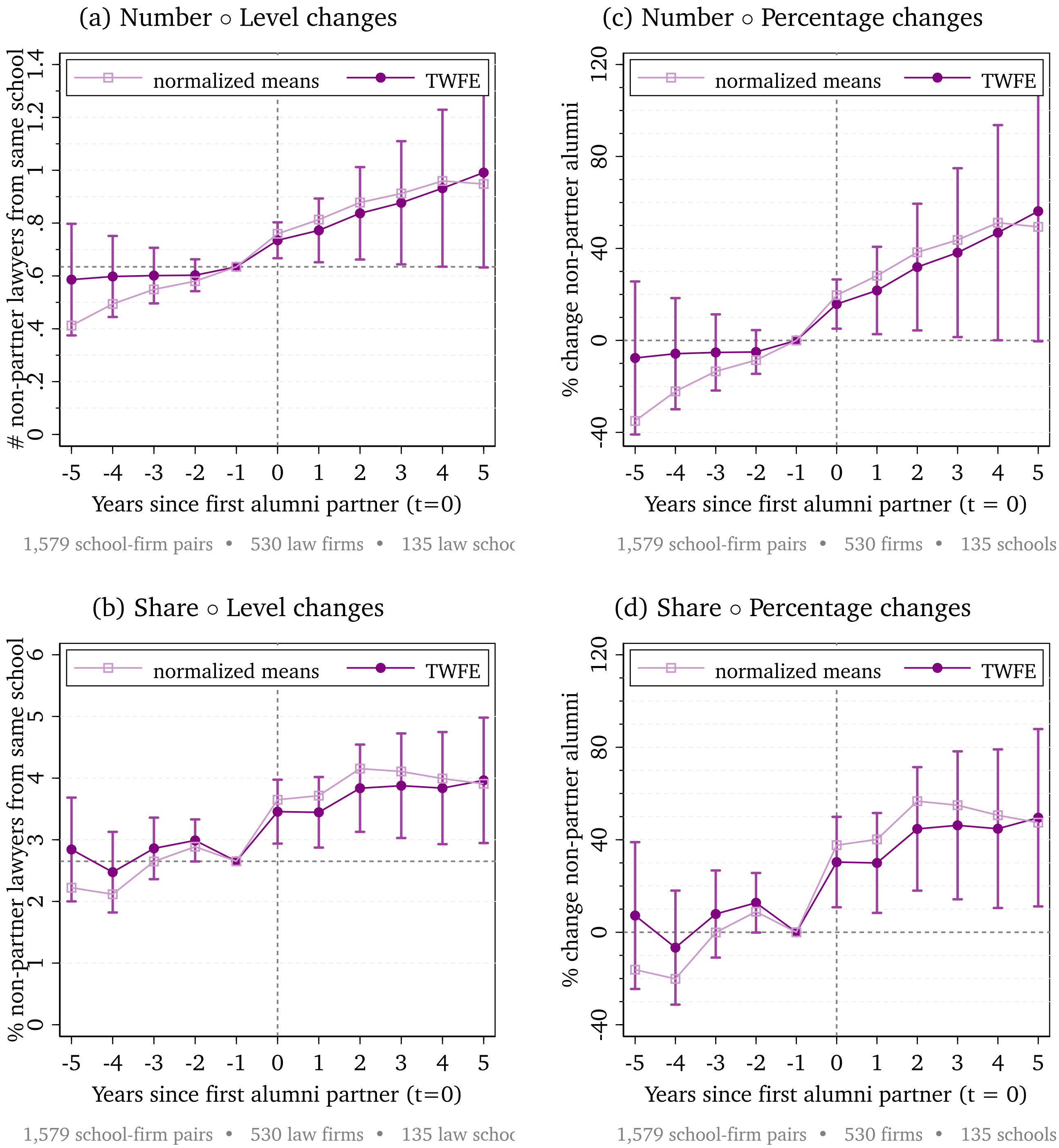
Notes: This figure displays the distributions of law firms (left panel) and law school (right panel) based on the average yearly number of job spells in the main analysis sample. Small-size firms have 15 or fewer lawyer spells, medium-size firms have 16-50 lawyer spells, and large-size firms more than 50 lawyer spells. Small-network schools have 20 or fewer lawyer spells, medium-size schools have 21-50 lawyer spells, and large-network schools more than 50 lawyer spells. See Appendix Figure A.2 for the distribution of firms and schools with 100+ lawyer spells.

Figure 2: "Leave-one out" number of junior lawyers from the same school



Notes: In each subfigure, the dotted line represents the first observed partner from the school at the firm listed in the title. The school and firm rankings shown in parentheses in the title are based on the yearly average number of lawyer spells.

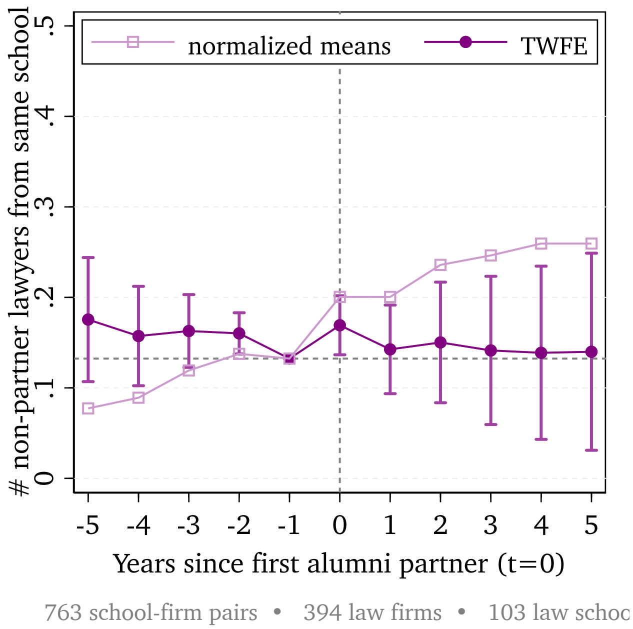
FIGURE 3: Event study around the first observed alum partner
Sample: All schools and all firms



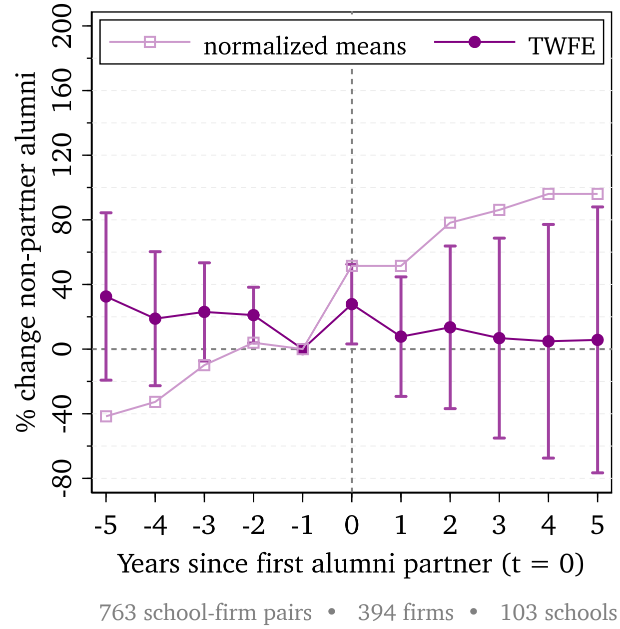
Notes: This figure shows the evolution of the number (top subfigures) and share (bottom subfigures) of non-partner (i.e., junior) lawyers from the same school around the first observed partner from that school. Sample includes all firms and all schools. The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specifications (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 4: Event study around the first observed alum partner
Sample: Small-size firms ($\leq$ 15 lawyers per year on average)

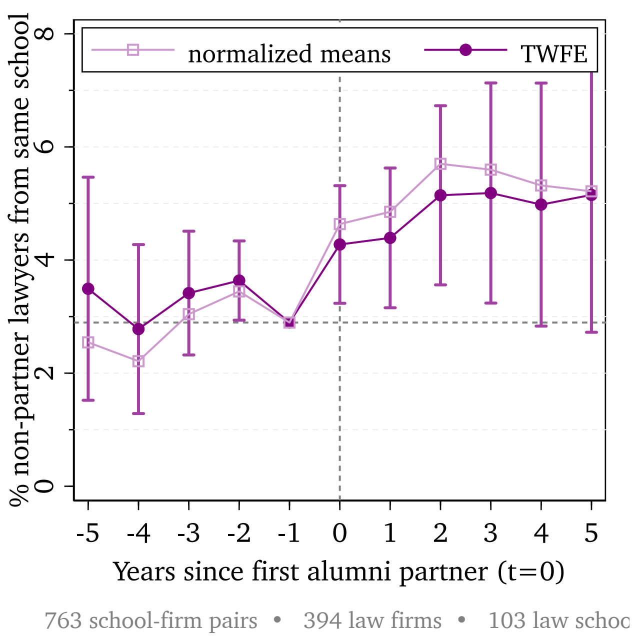
(a) Number ∘ Level changes



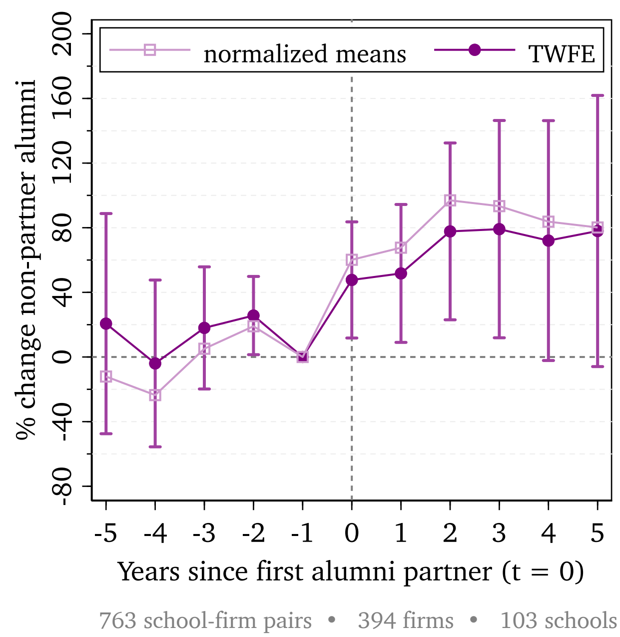
(c) Number ∘ Percentage changes



(b) Share ∘ Level changes

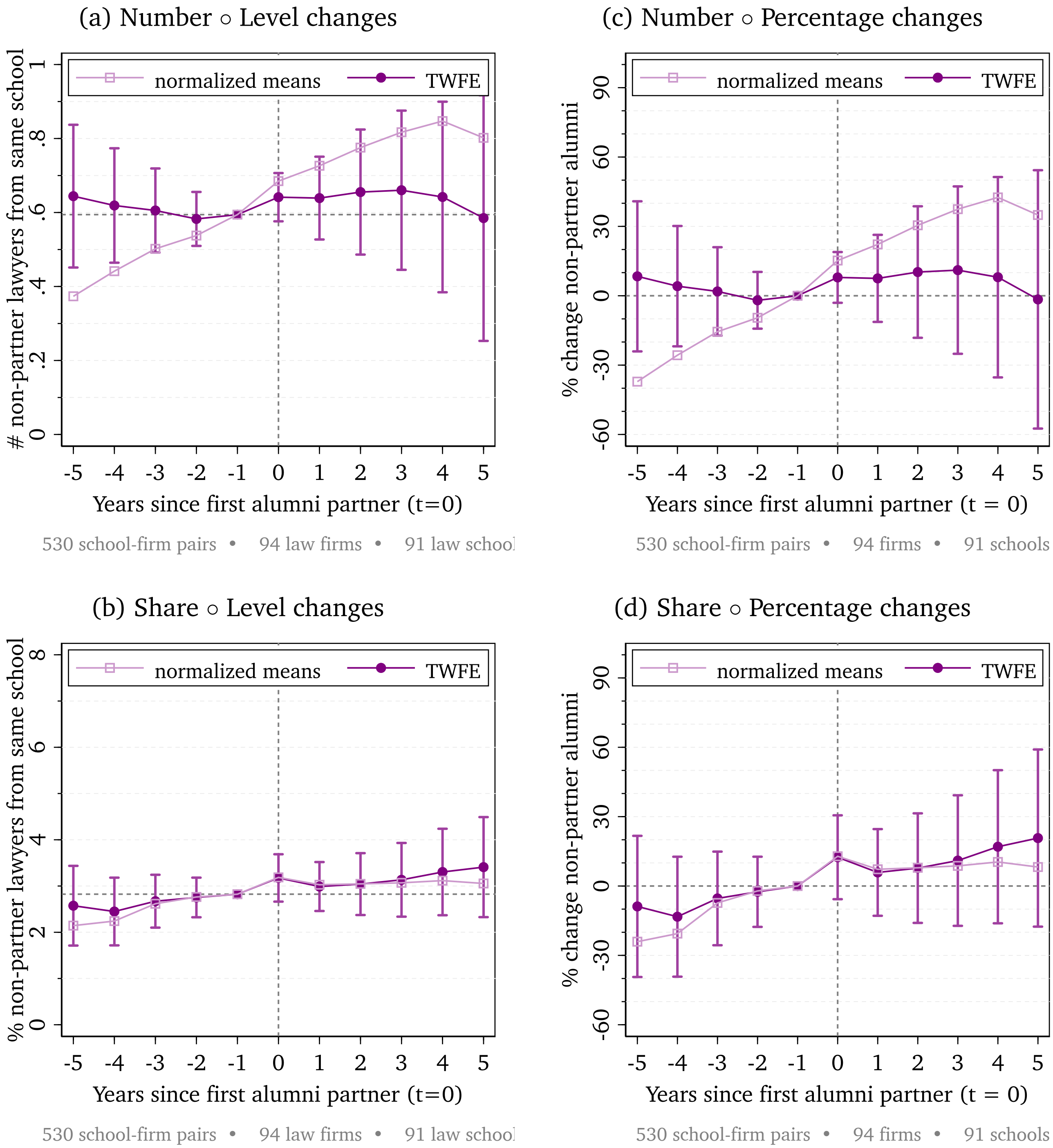


(d) Share ∘ Percentage changes



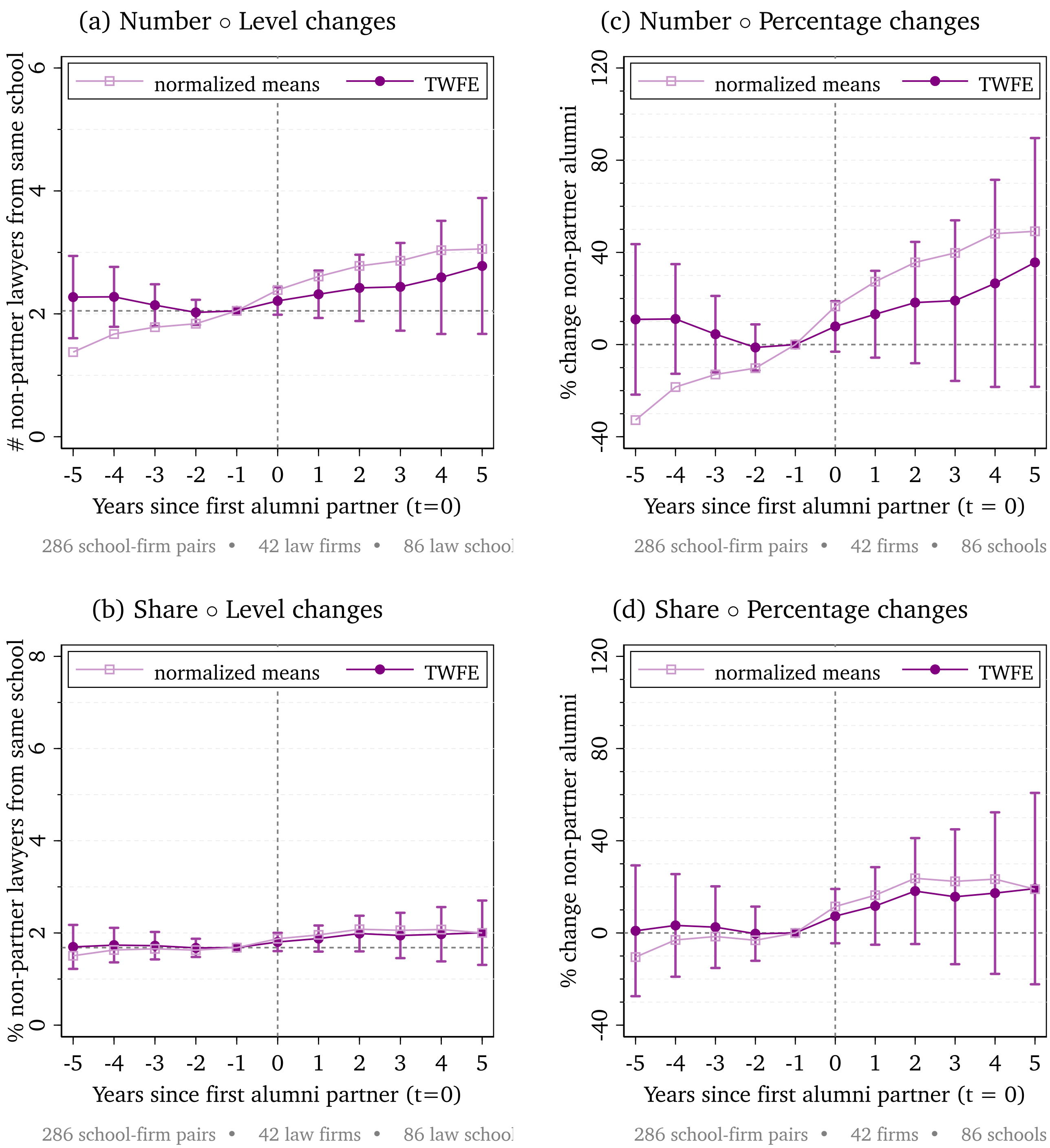
Notes: This figure replicates Figure 3 but restricts the sample to small-size law firms (i.e., 15 or fewer lawyers per year on average). The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 5: Event study around the first observed alum partner
Sample: Mid-size firms (16-50 lawyers per year on average)



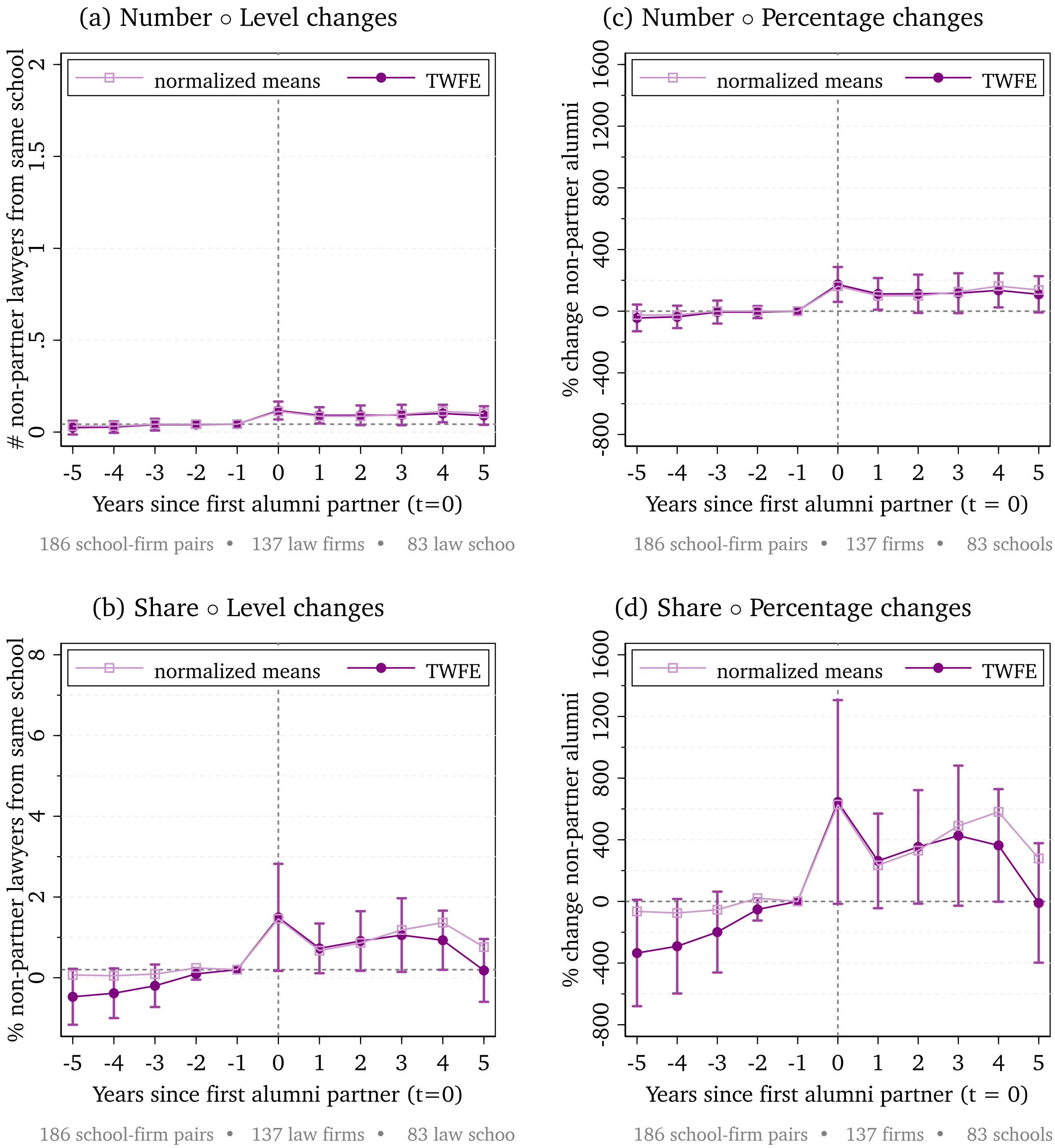
Notes: This figure replicates Figure 3 but restricts the sample to mid-size law firms (i.e., 16-50 lawyers per year on average). The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 6: Event study around the first observed alum partner
Sample: Large-size firms (> 50 lawyers per year on average)



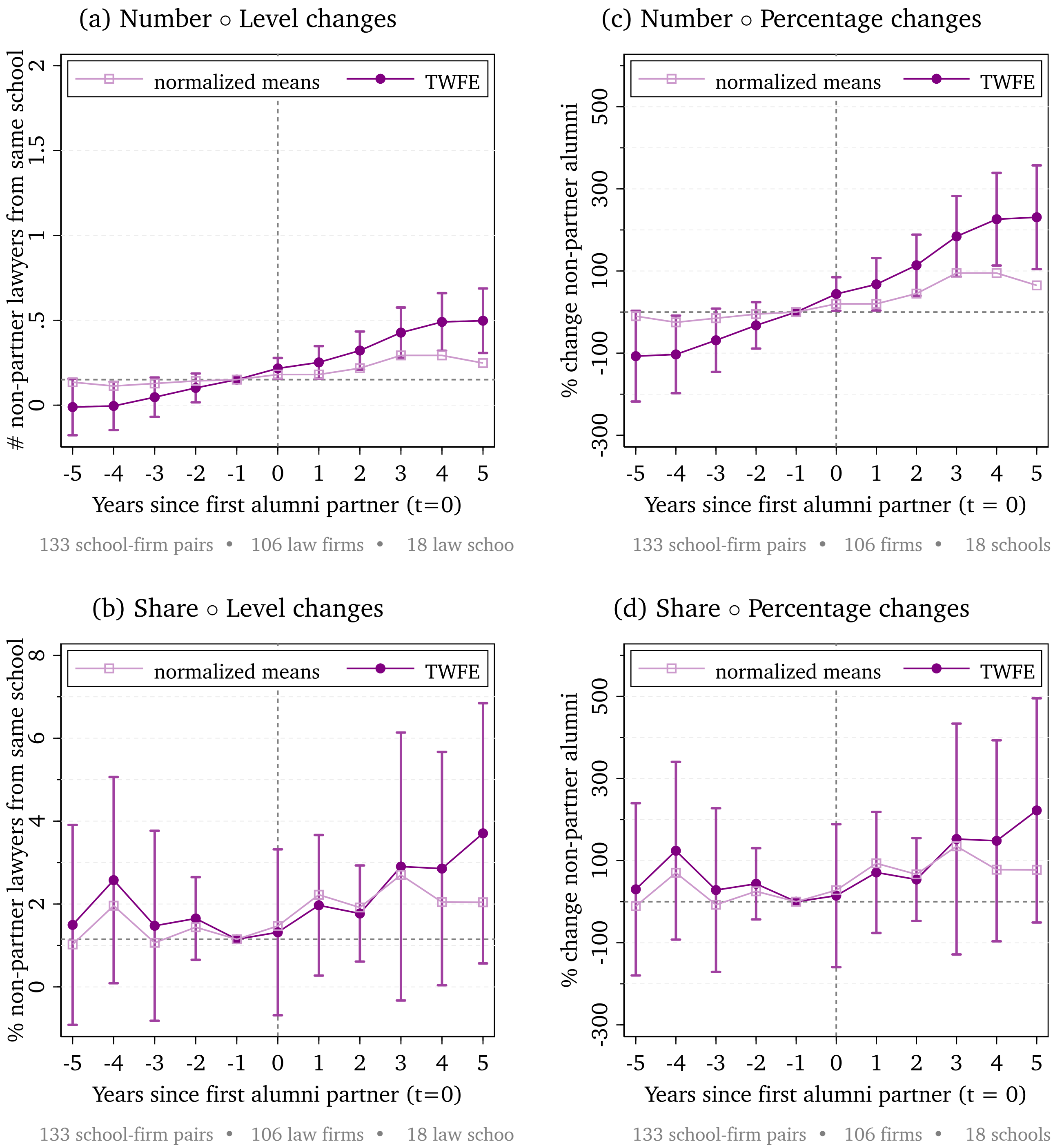
Notes: This figure replicates Figure 3 but restricts the sample to large-size law firms (i.e., more than 50 lawyers per year on average). The y-axis displays “leave-one-out” numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted (“leave-one-out”) to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 7: Event study around the first observed alum partner
Sample: Small-network schools (≤ 20 lawyers per year on average)



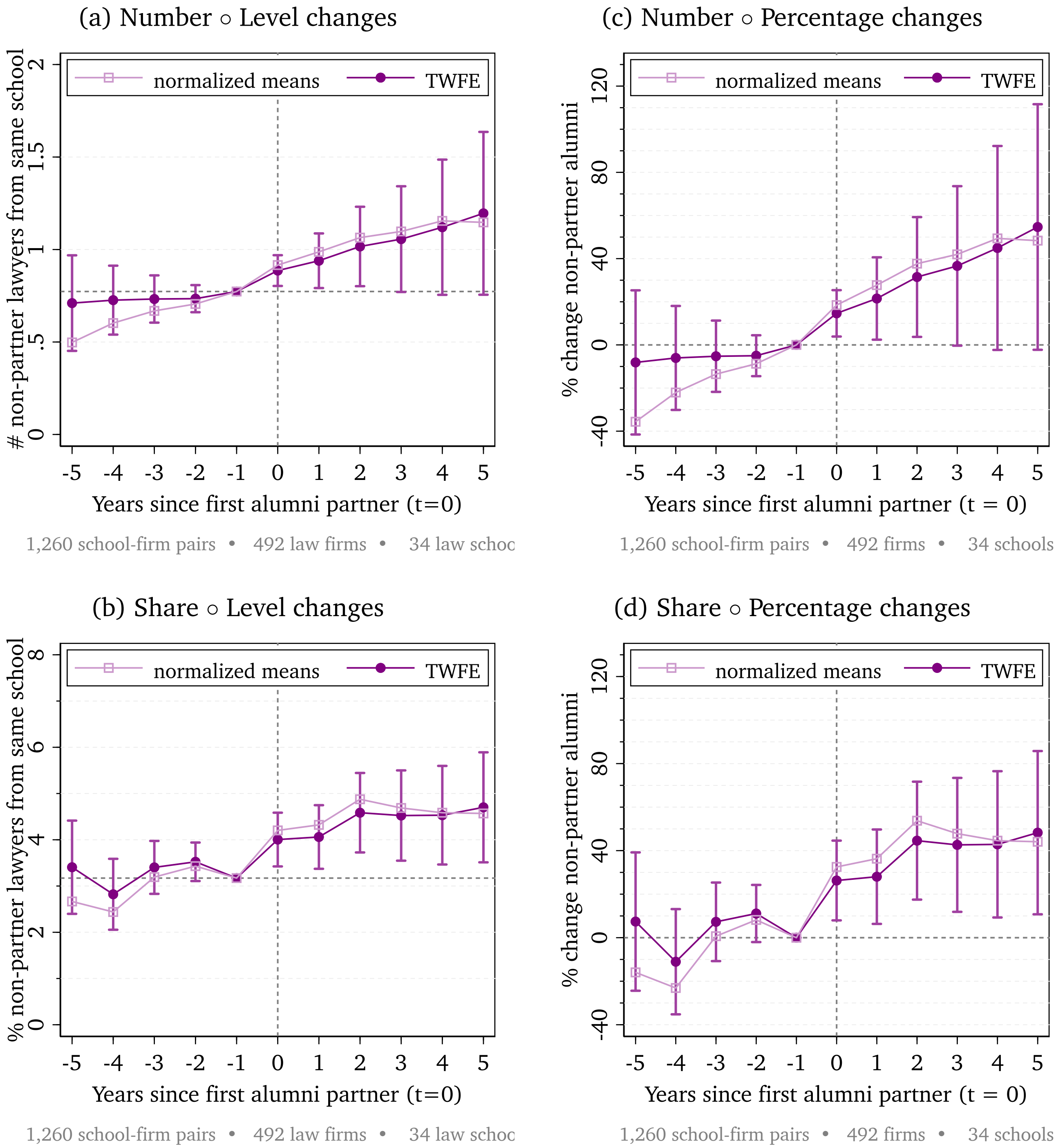
Notes: This figure replicates Figure 3 but restricts the sample to small-network law schools (i.e., 20 or fewer lawyers per year on average). The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 8: Event study around the first observed alum partner
Sample: Medium-network schools (21-50 lawyers per year on average)



Notes: This figure replicates Figure 3 but restricts the sample to mid-network law schools (i.e., 21-50 lawyers per year on average). The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

FIGURE 9: Event study around the first observed alum partner
Sample: Large-network schools (> 50 lawyers per year on average)



Notes: This figure replicates Figure 3 but restricts the sample to large-network law schools (i.e., more than 50 lawyers per year on average). The y-axis displays "leave-one-out" numbers (top subfigures) and shares (bottom subfigures) – i.e., I exclude any potential junior lawyers who got promoted ("leave-one-out") to avoid a mechanical decrease in the number/share of junior lawyers following a promotion. In the percentage changes specification (right subfigures), all the coefficients shown have been normalized to 0 for the year before the first alum partner ($t = -1$) – i.e., all the coefficients are with respect to the one at $t = -1$. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

TABLE 1: Internal job promotion ("make partner") and presence of an alum partner when spell ended
Sample: All company-school pairs

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Alum partner (=1)	0.14***	0.14***	0.14***	0.15***	0.15***
	(0.0060)	(0.0059)	(0.0067)	(0.0070)	(0.0078)
Female (=1)		-0.0092*			-0.0093*
		(0.0051)			(0.0056)
Nonwhite (=1)		0.016***			0.020***
		(0.0055)			(0.0062)
Years of experience		0.0083***			0.0097***
		(0.00076)			(0.00087)
Firm size: # lawyers			0.00052***		0.00018
			(0.00016)		(0.00016)
Firm size: # partners			-0.0034***		-0.0016**
			(0.00060)		(0.00067)
School network size: # lawyers				0.00056***	-0.00017
				(0.000089)	(0.00011)
School network size: # partners				-0.0017***	0.000055
				(0.00023)	(0.00031)
Constant	0.032***	-0.063***	0.045***	-0.019	0.0052
	(0.0021)	(0.0093)	(0.012)	(0.019)	(0.032)
Adjusted R^2	0.056	0.088	0.066	0.063	0.099
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations			11,134		
Number of individuals			8,927		
Number of firms			1,074		
Number of schools			187		

Notes: "Alum partner (=1)" is a binary variable that takes value one if there is an alum partner the year before the newly promoted associate starts its partner role, and zero otherwise. "Subsequently internally promoted (=1)" is an indicator variable that takes value one if the associate's next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school and who have obtained their J.D. from 2000 onwards. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

TABLE 2: Internal job promotion ("make partner") and presence of an alum partner when spell ended
Sample: Company-school pairs that never had an alum partner before the spell start

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Alum partner (=1)	0.29***	0.28***	0.27***	0.29***	0.27***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Female (=1)		-0.0043			-0.0065
		(0.0057)			(0.0066)
Nonwhite (=1)		0.017***			0.022***
		(0.0063)			(0.0074)
Years of experience		0.0049***			0.0062***
		(0.00081)			(0.00098)
Firm size: # lawyers			0.00037**		0.00016
			(0.00018)		(0.00018)
Firm size: # partners			-0.0028***		-0.0025***
			(0.00077)		(0.00085)
School network size: # lawyers				0.00043***	-0.00019
				(0.00012)	(0.00016)
School network size: # partners				-0.0012***	0.00018
				(0.00032)	(0.00044)
Constant	0.030***	-0.031***	0.043***	-0.0095	0.035
	(0.0022)	(0.010)	(0.012)	(0.019)	(0.032)
Adjusted R^2	0.159	0.178	0.157	0.159	0.177
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations			7,309		
Number of individuals			6,155		
Number of firms			1,056		
Number of schools			187		

Notes: "Alum partner (=1)" is a binary variable that takes value one if there is an alum partner the year before the newly promoted associate starts its partner role, and zero otherwise. "Subsequently internally promoted (=1)" is an indicator variable that takes value one if the associate's next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school, who have obtained their J.D. from 2000 onwards, and who are working at a law firm that ever had an alum partner. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

TABLE 3: Internal job promotion ("make partner") and presence of an alum partner when spell ended
Sample: Company-school pairs that already had an alum partner before the spell start

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Alum partner (=1)	0.065***	0.068***	0.055***	0.064***	0.053***
	(0.010)	(0.010)	(0.013)	(0.010)	(0.013)
Female (=1)		-0.016*			-0.011
		(0.0095)			(0.010)
Nonwhite (=1)		0.011			0.011
		(0.010)			(0.011)
Years of experience		0.011***			0.013***
		(0.0015)			(0.0016)
Firm size: # lawyers			0.0010***		0.00042
			(0.00034)		(0.00036)
Firm size: # partners			-0.0040***		-0.00076
			(0.0010)		(0.0012)
School network size: # lawyers				0.00073***	-0.00023
				(0.00013)	(0.00020)
School network size: # partners				-0.0019***	0.00034
				(0.00032)	(0.00056)
Constant	0.046***	-0.075***	0.023	-0.090*	-0.020
	(0.0084)	(0.019)	(0.036)	(0.046)	(0.097)
Adjusted R^2	0.006	0.049	0.028	0.014	0.067
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations	3,825				
Number of individuals	3,304				
Number of firms	331				
Number of schools	61				

Notes: "Alum partner (=1)" is a binary variable that takes value one if there is an alum partner the year before the newly promoted associate starts its partner role, and zero otherwise. "Subsequently internally promoted (=1)" is an indicator variable that takes value one if the associate's next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school, who have obtained their J.D. from 2000 onwards, and who are working at a law firm that ever had an alum partner. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

TABLE 4: Internal job promotion ("make partner") and years of overlap with alum partner
Sample: All company-school pairs

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Overlap with alum partner (years)	0.0098***	0.0098***	0.0088***	0.0092***	0.0078***
	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0014)
Female (=1)		-0.0083			-0.0087
		(0.0052)			(0.0057)
Nonwhite (=1)		0.016***			0.021***
		(0.0057)			(0.0063)
Years of experience		0.0074***			0.0095***
		(0.00078)			(0.00088)
Firm size: # lawyers			0.00058***		0.00022
			(0.00016)		(0.00016)
Firm size: # partners			-0.0027***		-0.00081
			(0.00059)		(0.00067)
School network size: # lawyers				0.00060***	-0.00012
				(0.000089)	(0.00012)
School network size: # partners				-0.0016***	-0.000023
				(0.00023)	(0.00031)
Constant	0.070***	-0.014	0.063***	-0.010	0.019
	(0.0029)	(0.0093)	(0.012)	(0.019)	(0.032)
Adjusted R^2	0.009	0.039	0.026	0.012	0.057
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations			11,134		
Number of individuals			8,927		
Number of firms			1,074		
Number of schools			187		

Notes: "Overlap with alum partner (years)" is the number of years (computed as the number of months divided by 12) of overlap with at least one alum partner. "Subsequently internally promoted (=1)" is an indicator variable that takes value one if the associate's next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school and who have obtained their J.D. from 2000 onwards. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

TABLE 5: Internal job promotion ("make partner") and years of overlap with alum partner
Sample: Company-school pairs that never had an alum partner before the spell start

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Overlap with alum partner (years)	0.020***	0.020***	0.018***	0.019***	0.016***
	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0030)
Female (=1)		-0.0062			-0.0070
		(0.0062)			(0.0070)
Nonwhite (=1)		0.019***			0.024***
		(0.0067)			(0.0078)
Years of experience		0.0052***			0.0070***
		(0.00087)			(0.0011)
Firm size: # lawyers			0.00040**		0.00017
			(0.00018)		(0.00018)
Firm size: # partners			-0.0021***		-0.0014
			(0.00077)		(0.00086)
School network size: # lawyers				0.00049***	-0.00016
				(0.00012)	(0.00016)
School network size: # partners				-0.0012***	0.00012
				(0.00033)	(0.00045)
Constant	0.068***	0.0033	0.067***	0.0066	0.041
	(0.0031)	(0.011)	(0.012)	(0.019)	(0.033)
Adjusted R^2	0.014	0.040	0.035	0.013	0.058
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations			7,309		
Number of individuals			6,155		
Number of firms			1,056		
Number of schools			187		

Notes: "Overlap with alum partner (years)" is the number of years (computed as the number of months divided by 12) of overlap with at least one alum partner. "Subsequently internally promoted (=1)" is an indicator variable that takes value one if the associate's next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school, who have obtained their J.D. from 2000 onwards, and who are working at a law firm that ever had an alum partner. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

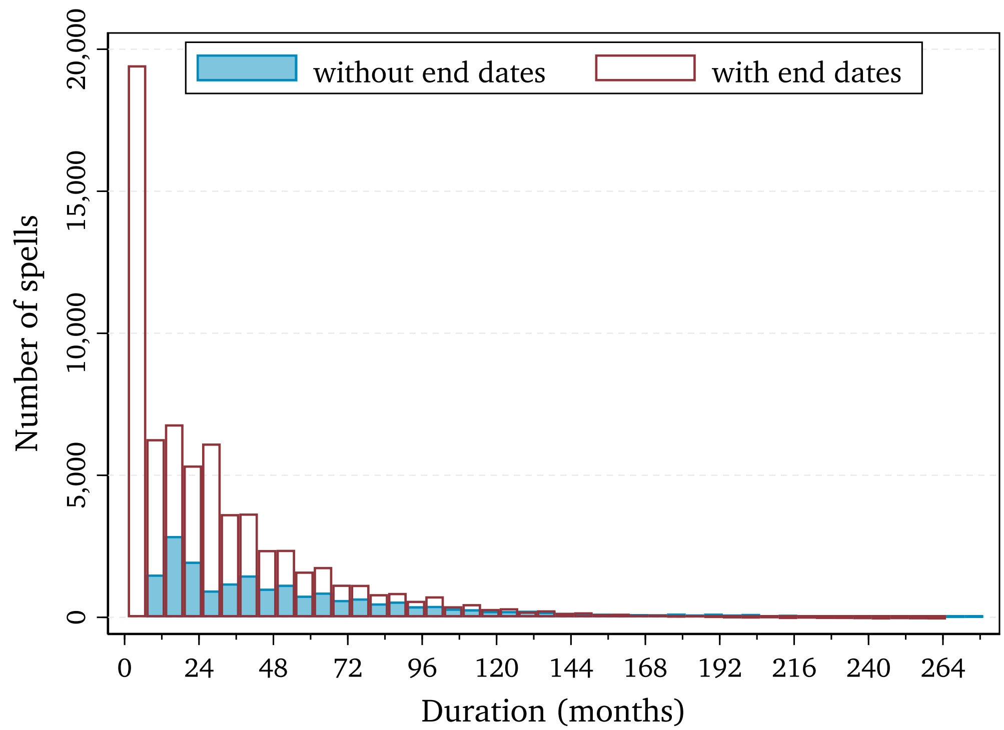
TABLE 6: Internal job promotion (“make partner”) and years of overlap with alum partner
Sample: Company-school pairs that already had an alum partner before the spell start

Dependent variable:	Subsequently internally promoted (=1)				
Controls:	None	Individual	Firm	School	All
	(1)	(2)	(3)	(4)	(5)
Overlap with alum partner (years)	0.0073***	0.0058***	0.0073***	0.0065***	0.0048**
	(0.0017)	(0.0017)	(0.0019)	(0.0018)	(0.0020)
Female (=1)		-0.015			-0.011
		(0.0095)			(0.010)
Nonwhite (=1)		0.011			0.010
		(0.010)			(0.011)
Years of experience		0.011***			0.013***
		(0.0015)			(0.0016)
Firm size: # lawyers			0.0011***		0.00049
			(0.00034)		(0.00036)
Firm size: # partners			-0.0039***		-0.00048
			(0.0010)		(0.0012)
School network size: # lawyers				0.00073***	-0.00021
				(0.00013)	(0.00020)
School network size: # partners				-0.0019***	0.00033
				(0.00032)	(0.00056)
Constant	0.072***	-0.036**	0.027	-0.067	-0.020
	(0.0076)	(0.018)	(0.035)	(0.045)	(0.097)
Adjusted R^2	0.005	0.046	0.029	0.012	0.066
Firm fixed effects	No	No	Yes	No	Yes
School fixed effects	No	No	No	Yes	Yes
Year fixed effects	No	Yes	No	No	Yes
Number of observations			3,825		
Number of individuals			3,304		
Number of firms			331		
Number of schools			61		

Notes: “Overlap with alum partner (years)” is the number of years (computed as the number of months divided by 12) of overlap with at least one alum partner. “Subsequently internally promoted (=1)” is an indicator variable that takes value one if the associate’s next role is partner in the same firm, and zero otherwise. Dataset at the spell level, where a spell is defined as the duration of a given role (i.e., a job title-company pair). Analysis sample includes all non-partner lawyer spells for lawyers who are at least six years out of law school, who have obtained their J.D. from 2000 onwards, and who are working at a law firm that ever had an alum partner. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

A Appendix Figures

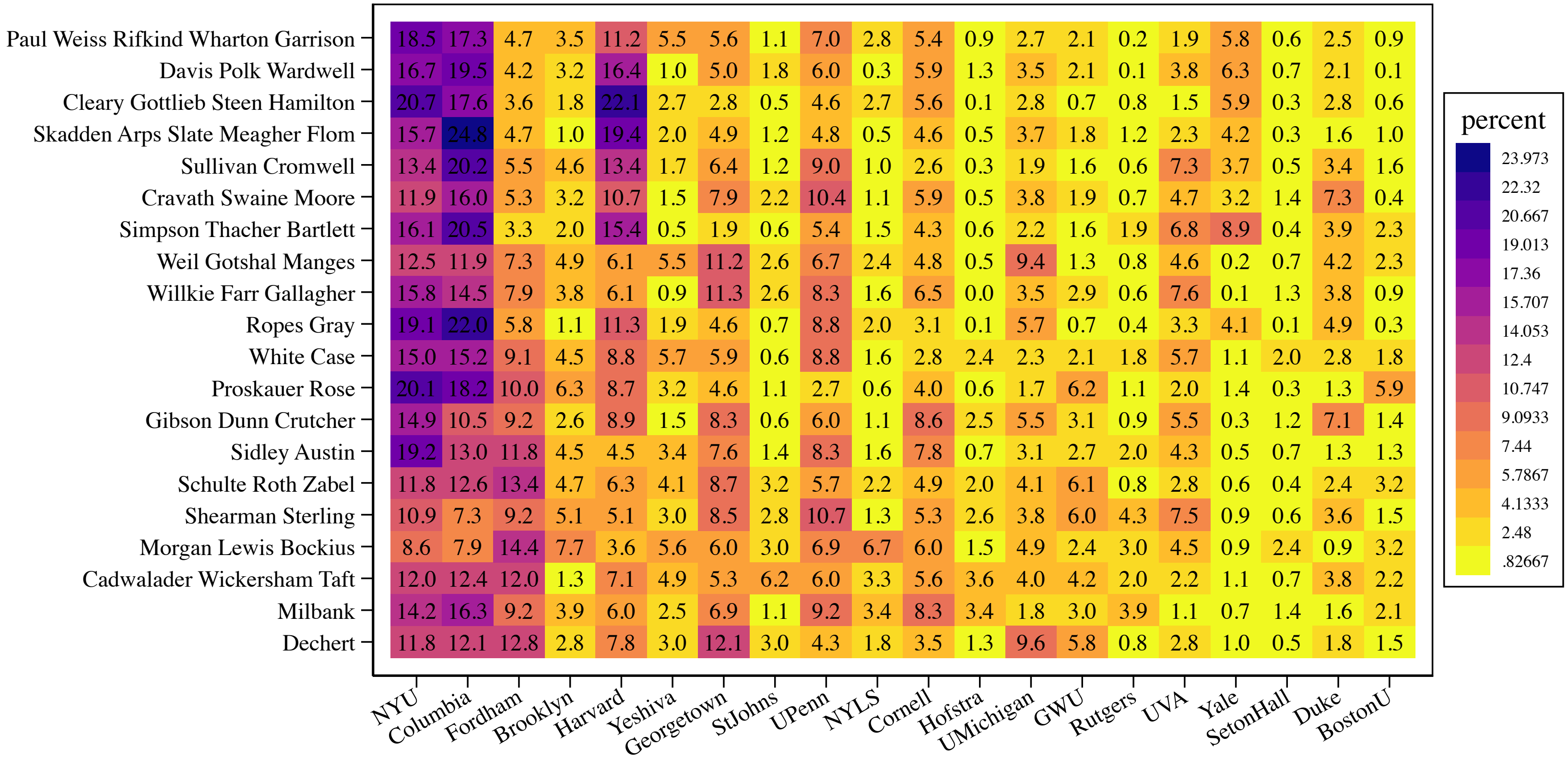
Appendix Figure A.1: Distribution of spell duration, with and without end dates



Notes: mean duration = 40 months; median duration = 25 months.

APPENDIX FIGURE A.2: NON-RANDOM ALLOCATION OF ALUMNI ACROSS THE LARGEST LAW FIRMS

(a) Within a large law firm, what % of *lawyer* spells are occupied by the alumni of a large-network school?



Notes: This figure displays the share of lawyers within a given law firm (listed on the y-axis) who graduated from a given law school (listed on the x-axis). The law firms are ranked from top to bottom based on the average yearly number of spells, in descending order. Similarly, the law schools are ranked from left to right based on the average yearly number of spells, in descending order. For example, the top-left cell indicates that 18.5% of lawyer spells at Paul Weiss Rifkind Wharton Garrison LLP law firm graduated from New York University (NYU). Within each row, the numbers do not necessarily sum to 100% because not all schools are listed. Only the shares for the top 20 law firms and top 20 law schools are shown.

APPENDIX FIGURE A.1: NON-RANDOM ALLOCATION OF ALUMNI ACROSS THE LARGEST LAW FIRMS (CONT'D)

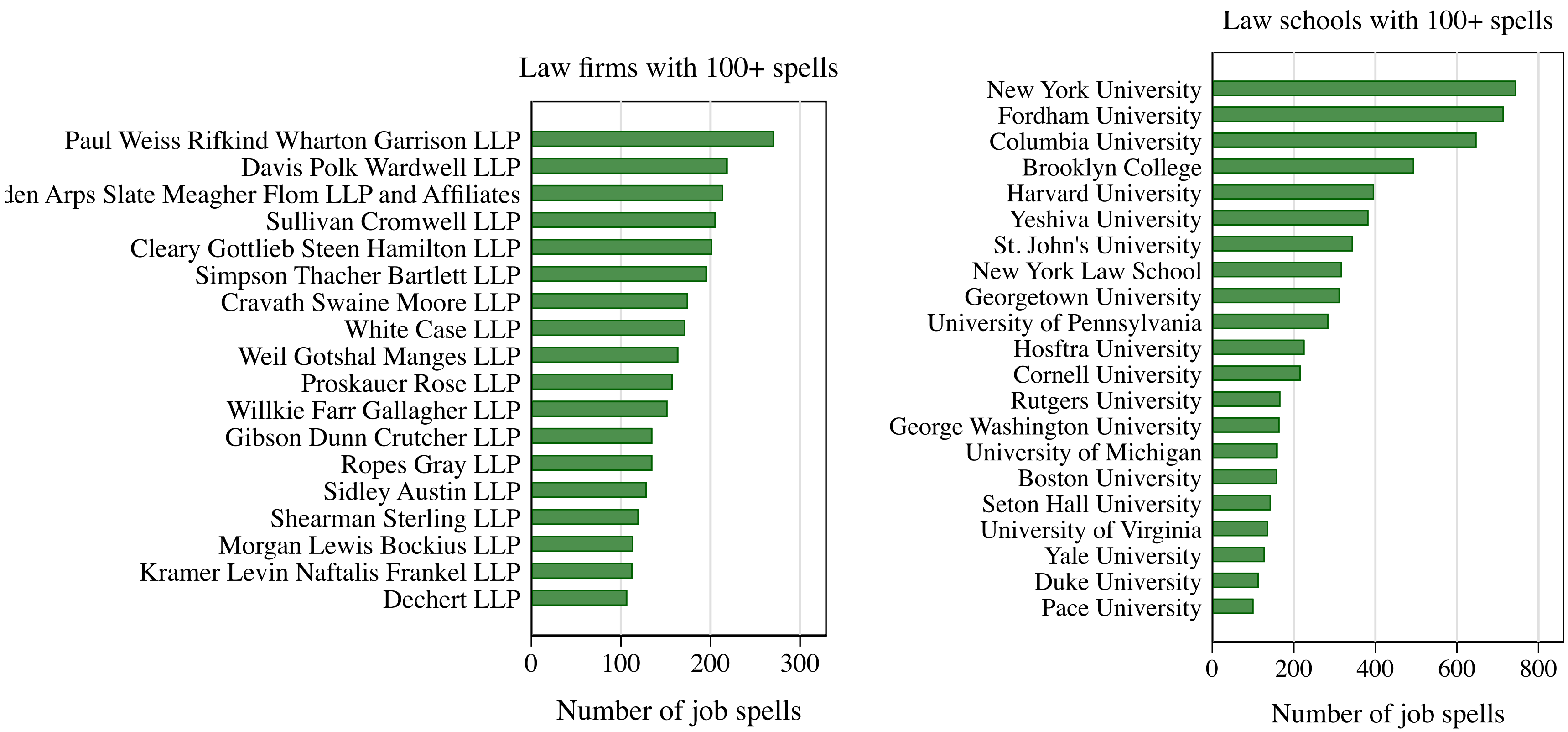
(b) Within a large law firm, what % of *partner* spells are occupied by the alumni of a large-network school?

	NYU	Columbia	Fordham	Brooklyn	Harvard	Yeshiva	Georgetown	StJohns	UPenn	NYLS	Cornell	Hofstra	UMichigan	GWU	Rutgers	UVA	Yale	SetonHall	Duke	BostonU
Paul Weiss Rifkind Wharton Garrison	11.6	7.2	7.2	7.2	11.6	1.4	7.2	1.4	10.1	0.0	4.3	0.0	8.7	1.4	0.0	4.3	1.4	4.3	8.7	1.4
Davis Polk Wardwell	18.3	8.3	8.3	5.0	5.0	0.0	10.0	3.3	15.0	0.0	6.7	1.7	1.7	5.0	5.0	1.7	5.0	0.0	0.0	0.0
Cleary Gottlieb Steen Hamilton	6.9	19.0	8.6	1.7	13.8	1.7	8.6	1.7	6.9	6.9	3.4	1.7	1.7	1.7	3.4	0.0	1.7	0.0	1.7	8.6
Skadden Arps Slate Meagher Flom	17.2	25.9	8.6	1.7	3.4	0.0	8.6	0.0	13.8	0.0	5.2	0.0	1.7	1.7	0.0	3.4	1.7	0.0	5.2	1.7
Sullivan Cromwell	14.3	16.1	14.3	5.4	8.9	5.4	1.8	0.0	8.9	1.8	5.4	0.0	5.4	1.8	1.8	0.0	5.4	1.8	0.0	1.8
Cravath Swaine Moore	18.9	24.5	11.3	0.0	18.9	0.0	0.0	0.0	7.5	1.9	5.7	0.0	1.9	0.0	0.0	3.8	1.9	0.0	0.0	3.8
Simpson Thacher Bartlett	21.6	9.8	17.6	0.0	5.9	3.9	5.9	0.0	0.0	2.0	7.8	2.0	0.0	9.8	2.0	5.9	0.0	2.0	0.0	3.9
Weil Gotshal Manges	16.3	18.6	7.0	2.3	23.3	4.7	4.7	0.0	2.3	0.0	2.3	0.0	0.0	2.3	0.0	2.3	11.6	0.0	2.3	0.0
Willkie Farr Gallagher	29.4	14.7	2.9	0.0	17.6	0.0	0.0	0.0	2.9	0.0	2.9	5.9	0.0	2.9	0.0	0.0	14.7	0.0	5.9	0.0
Ropes Gray	9.1	24.2	15.2	0.0	6.1	0.0	9.1	0.0	9.1	0.0	9.1	0.0	3.0	3.0	0.0	0.0	3.0	0.0	9.1	0.0
White Case	22.6	22.6	3.2	6.5	0.0	6.5	9.7	0.0	0.0	3.2	3.2	0.0	3.2	6.5	0.0	3.2	0.0	0.0	3.2	6.5
Proskauer Rose	13.3	23.3	6.7	3.3	6.7	3.3	0.0	0.0	3.3	6.7	10.0	0.0	3.3	10.0	0.0	0.0	10.0	0.0	0.0	0.0
Gibson Dunn Crutcher	13.8	34.5	3.4	0.0	24.1	3.4	3.4	0.0	3.4	0.0	3.4	0.0	0.0	0.0	6.9	0.0	3.4	0.0	0.0	0.0
Sidley Austin	17.9	7.1	17.9	3.6	14.3	0.0	7.1	3.6	0.0	3.6	7.1	0.0	3.6	0.0	0.0	7.1	0.0	0.0	0.0	7.1
Schulte Roth Zabel	3.7	7.4	11.1	7.4	14.8	11.1	3.7	0.0	3.7	3.7	0.0	3.7	0.0	3.7	3.7	0.0	14.8	0.0	0.0	7.4
Shearman Sterling	22.2	7.4	14.8	3.7	11.1	0.0	11.1	0.0	3.7	0.0	3.7	0.0	3.7	0.0	0.0	7.4	0.0	0.0	0.0	11.1
Morgan Lewis Bockius	12.0	20.0	4.0	0.0	24.0	0.0	8.0	4.0	4.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	8.0	0.0	4.0	8.0
Cadwalader Wickersham Taft	0.0	19.0	4.8	0.0	23.8	4.8	9.5	4.8	0.0	0.0	4.8	9.5	4.8	14.3	0.0	0.0	0.0	0.0	0.0	0.0
Milbank	42.1	5.3	5.3	5.3	26.3	0.0	0.0	0.0	10.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.3	0.0	0.0	0.0
Dechert	12.5	37.5	0.0	0.0	12.5	0.0	0.0	0.0	0.0	6.3	0.0	0.0	6.3	0.0	0.0	6.3	12.5	0.0	0.0	6.3

percent: 40.697, 37.89, 35.083, 32.277, 29.47, 26.663, 23.857, 21.05, 18.243, 15.437, 12.63, 9.8233, 7.0167, 4.21, 1.4033

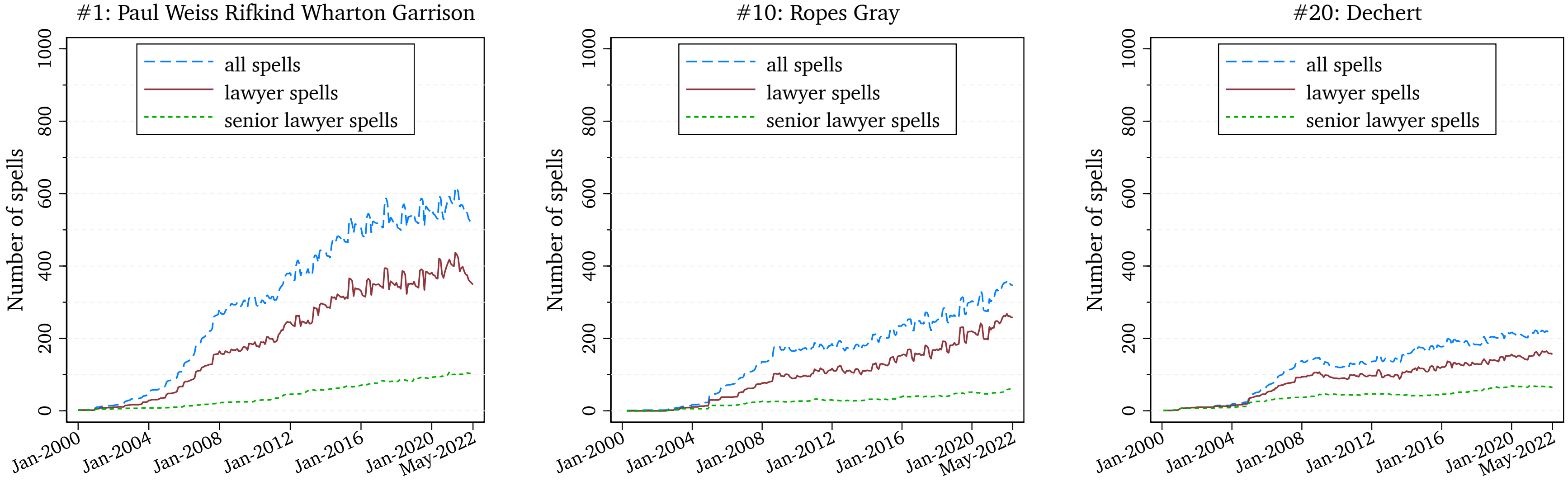
Notes: This figure displays the share of partners within a given law firm (listed on the y-axis) who graduated from a given law school (listed on the x-axis). The law firms are ranked from top to bottom based on the average yearly number of partner spells, in descending order. Similarly, the law schools are ranked from left to right based on the average yearly number of partner spells, in descending order. For example, the top-left cell indicates that 11.6% of partner spells at Paul Weiss Rifkind Wharton Garrison LLP law firm graduated from New York University (NYU). Within each row, the numbers do not necessarily sum to 100% because not all schools are listed. Only the shares for the top 20 law firms and top 20 law schools are shown.

Appendix Figure A.2: Subsamples of firms and schools with 100+ lawyer spells per year on average



Notes: This figure displays the distributions of law firms (left panel) and law school (right panel) based on the average yearly number of job spells in the main analysis sample, only for the firms and schools that have more than 100 lawyer spells per year on average.

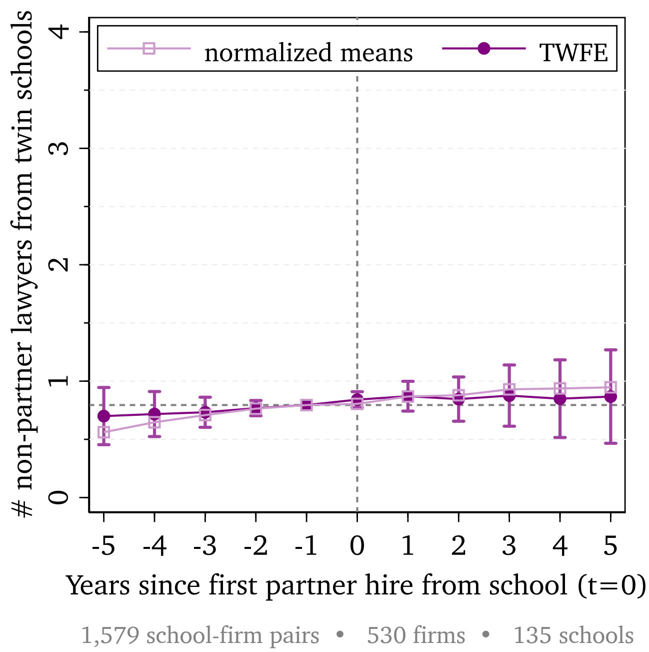
APPENDIX FIGURE A.3: TIME SERIES OF SPELLS AT 1ST, 10TH, AND 20TH LARGEST LLP LAW FIRMS



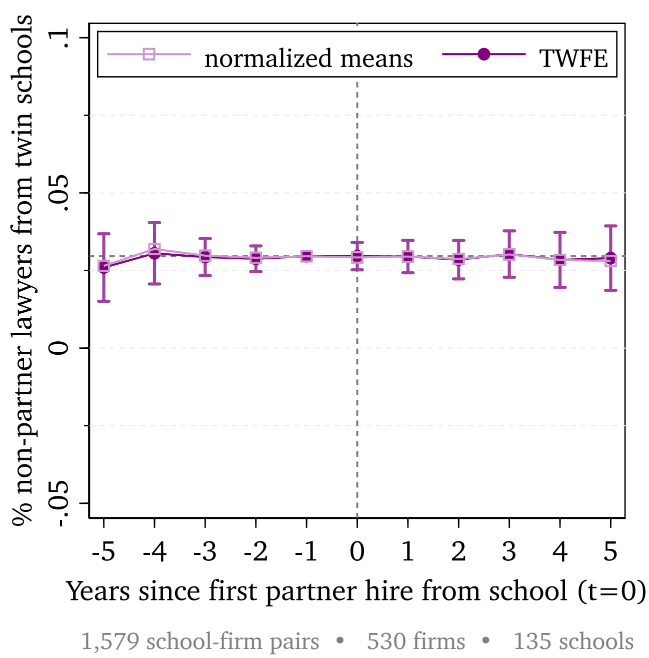
Notes: This figure displays the evolution over time of job spells, broken down by spell type, at the 1st (left panel), 10th (middle panel), and 20th (right panel) largest LLP law firm in the data. The size of the law firm is determined based on the average yearly number of spells. The long dashed blue lines represent all spells, the solid maroon lines represent the lawyer spells only, and the short dashed green lines represent the partner spells only.

APPENDIX FIGURE A.4: Placebo event study (in level changes) around the first observed alum partner
Sample: All firms & all schools

(a) Number

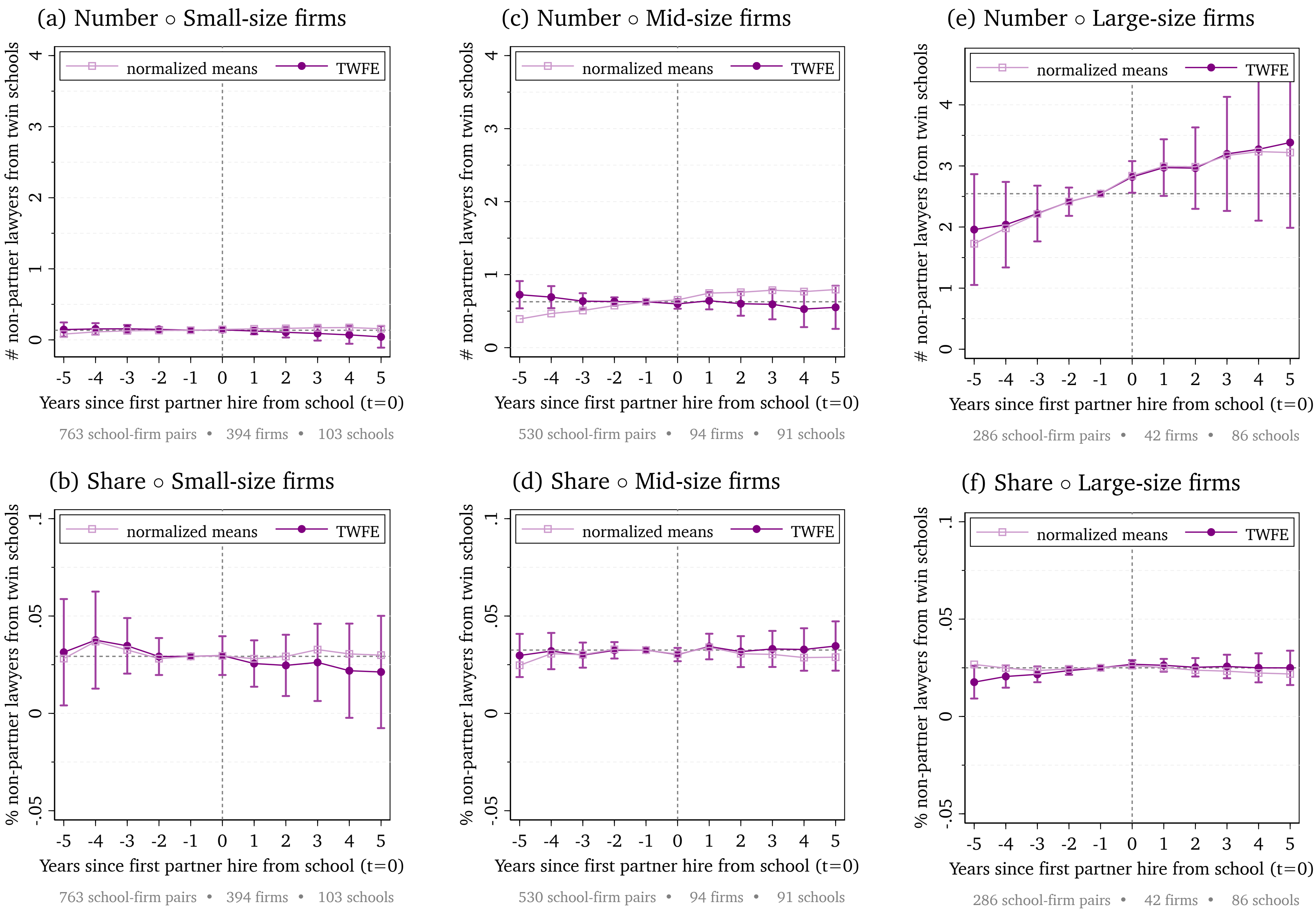


(b) Share



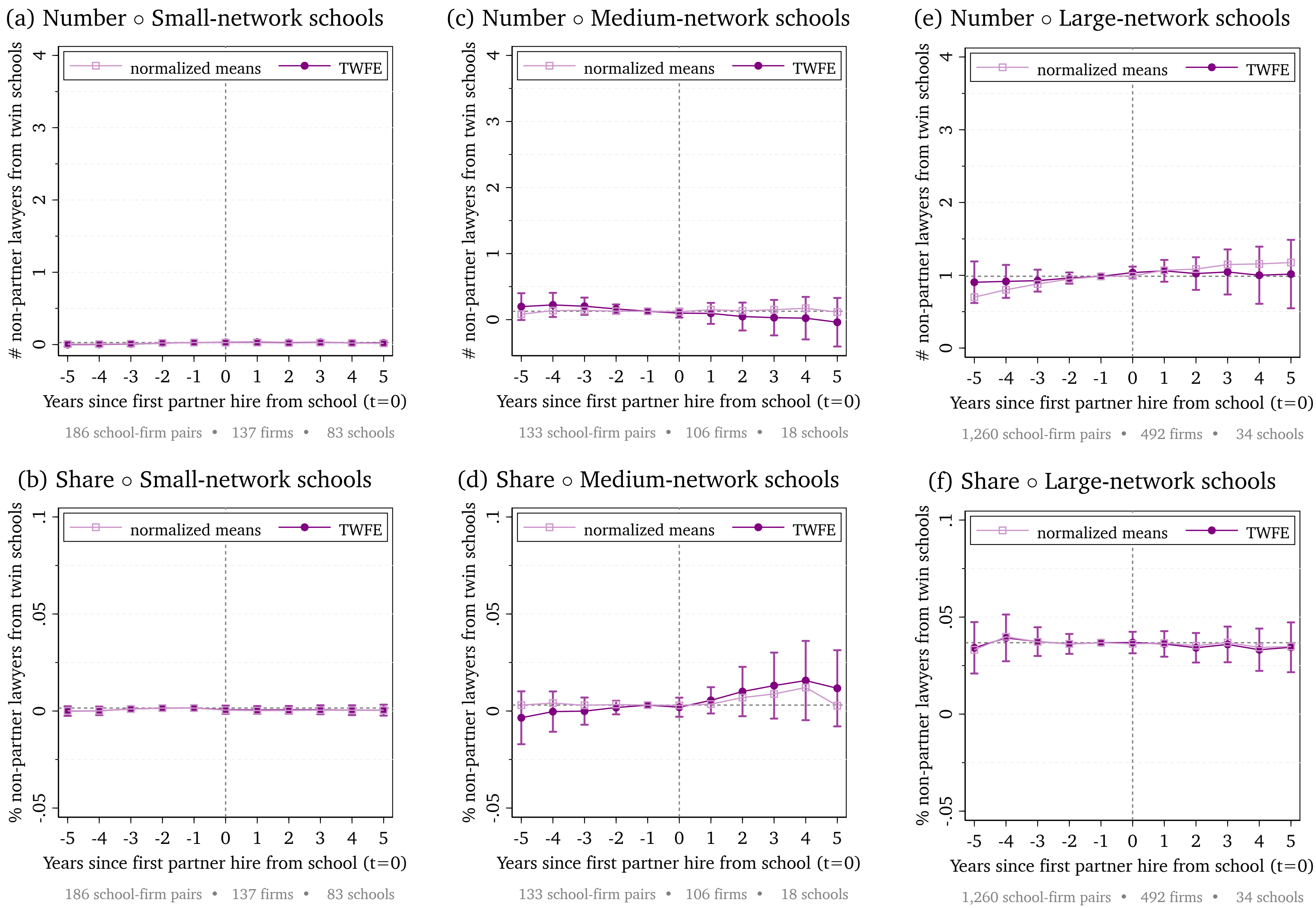
Notes: This figure shows the evolution of the number (subfigure (a)) and share (subfigure (b)) of non-partner (i.e., junior) lawyers from the *twin* school around the first observed partner from a given school. In other words, this figure replicates the left subfigures of Figure 3 but changes the y-axis to display the "leave-one-out" number/share of junior lawyers from their assigned *twin* school. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

APPENDIX FIGURE A.5: Placebo event study (in level changes) around the first observed alum partner, by firm size



Notes: This figure shows the evolution of the number (top subfigures) and share (bottom subfigures) of non-partner (i.e., junior) lawyers from the *twin* school around the first observed partner from a given school, for different firm size subsamples. In other words, this figure replicates the left subfigures of Figures 4-5-6 but changes the y-axis to display the "leave-one-out" number/share of junior lawyers from their assigned *twin* school. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

APPENDIX FIGURE A.6: Placebo event study (in level changes) around the first observed alum partner, by school-network size



Notes: This figure shows the evolution of the number (top subfigures) and share (bottom subfigures) of non-partner (i.e., junior) lawyers from the *twin* school around the first observed partner from a given school, for different school-network size subsamples. In other words, this figure replicates the left subfigures of Figures 7-8-9 but changes the y-axis to display the "leave-one-out" number/share of junior lawyers from their assigned *twin* school. The TWFE specification includes firm, school, and year fixed effects. Standard errors are clustered at the company-school level.

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