Exchanges of innovation resources inside venture capital portfolios

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Abstract

I explore the prevalence of exchanges of innovation resources inside venture capital portfolios. I show that after companies join investors' portfolios, several proxies of exchanges between them and portfolio companies (relative to matched nonportfolio companies) increase by an average of 60%. The increase holds when joining events are plausibly exogenous and when VCs' bargaining power and potential conflicts of interest are low. Three novel mechanisms are supported: carve-outs, spawning, and recycling, whereby entrepreneurs divest innovation units, start new ventures, and reuse assets in other portfolio companies, respectively. Results suggest that returns to innovation are higher in venture capital portfolios.

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1. Introduction

Young companies' difficulties in profiting from inventions have long been recognized by academics and policy makers alike. In almost all cases, the successful commercialization of an innovation requires the inventor's knowhow to be combined with other innovation resources that the original inventor lacks and seldom develops herself (Teece, 1994).[1] The challenge lies in the many frictions that can obstruct exchanges of innovation resources among young firms. For example, firms' investments may be constrained by information asymmetries, expropriation risk can prevent inventors from selling their inventions (cf. Arrow, 1975), and conflicts in arranging complete contracts can preclude trade (cf. Allen and Phillips, 2000).

In this paper, I explore the prevalence of exchanges of innovation resources between companies sharing common venture capitalists (VCs). As strategic investors, VCs have incentives to finance firms with complementary innovation resources in an effort to increase investment returns; for example, by internalizing innovation spillovers (cf. Teece, 1980; Hellman, 2002) or increasing product prices (cf. Azar, Schmalz, and Tecu, 2018). In theory, VCs can also facilitate innovation exchanges; for example, by punishing expropriation behavior (e.g., as advisors and board members; see Lerner, 1995 and Hellman and Puri, 2002), bridging information asymmetries (e.g., in their role of screeners and monitors; see Sørensen, 2007 and Kaplan and Stromberg, 2001, 2002), or financing otherwise constrained firms. In practice, however, competition for investors could also obstruct collaboration inside investors' portfolios (cf. Fulghieri and Sevilir, 2009). Ultimately, how prevalent exchanges of innovation resources are inside VC portfolios is an open question.

The main obstacle in exploring this question is that directly observing exchanges of innovation resources, especially among young, private companies (the usual targets of VCs) is not possible: no public markets for innovation resources exist. However, I can, and do, look for empirical evidence inside venture capital portfolios of measurable cross-company interactions that typically lead to the successful commercialization of industrial innovations (as validated by prior work), such as patent citations (Hall, Jaffe, and Trajtenberg, 2005; Kogan et al., 2017), patent reassignments (Akcigit, Celik,

[1] For instance, the commercialization of computer hardware typically requires specialized software.

and Greenwood, 2015; Serrano, 2010; Hochberg, Serrano, and Ziedonis, 2018), worker mobility (Almeida and Kogut, 1999; Kaiser, Kongsted, and Rønde, 2015; Azoulay, Graff Zivin, and Sampat, 2012), strategic alliances (Mowery, Oxley, and Silverman, 1996; Stuart, 2000; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), and mergers and acquisitions (cf. Teece, 2010; Seru, 2014). I use an event time framework that exploits differences in both the timing when and the investors from which companies secure venture capital. I focus on innovative US companies that were financed by US VCs, and filed at least one patent in the US Patent and Trademark Office during the 1976-2008 period.

The results show that after companies join the portfolio of a VC for the first time, several proxies of exchanges of innovation resources between them and other companies in the VC's portfolio (portfolio exchanges) increase by an average of 60% (over the sample mean) relative to exchanges between them and matched nonportfolio companies (nonportfolio exchanges). The increase holds for both portfolio exchanges led by joiners and those led by portfolio firms, and is robust to excluding companies with within-portfolio alliances (cf. Lindsey, 2008). The data support three novel mechanisms of within-portfolio exchange: carve-outs—whereby restructuring companies divest some of their innovation units inside the portfolio, spawning—whereby entrepreneurs move on to start new companies also financed by the same VCs, and recycling—whereby the residual assets of restructured companies are absorbed by other portfolio firms.

My interpretation of these results is that portfolio exchanges can be facilitated and used as a basis for investment selection by VCs. Consistent with potential selection effects, there is evidence that some portfolio exchanges begin to increase before the joiners enter the portfolio. On the other hand, the relative increase in portfolio exchanges is concentrated in some situations where, absent common VCs, such exchanges may not arise. For example, the increase is larger for exchanges financed by portfolio companies that are in the same industries as joiners, and thus possibly subject to expropriation risk and negative product rivalry effects, unless a common VC serves as arbiter.

Other more mechanical explanations are less consistent with the findings. For example, potential industry, scale, technology, and location clustering effects have limited ability to explain the results. Nonportfolio and portfolio companies are matched by technological focus, size, industry, and geography, and any fixed differences between them are absorbed by the difference-in-differences nature of the methodology. Unobserved differences between companies in and out of the venture capital industry cannot explain the findings either: results continue to hold when I instead use a matching methodology based on amounts of venture funds raised as well as company age, location, and technology. A battery of robustness checks shows that results are also not driven by influential observations at the state, firm, or company levels or by serial correlation and spurious trends.

The main implication of the results is that exchanges of innovation resources appear prevalent in venture capital portfolios. As the successful commercialization of inventions typically requires such exchanges, results suggest that returns are higher when innovations are backed by VCs.[2] This suggestion is consistent with the salience of VCs in the finance of high-value innovation: since the 1980s, patents awarded to venture capital-backed companies amount to circa 6% of US patent grants and command twice as many citations (a standard proxy of innovation value) as patents awarded to other types of owners (see Online Appendix 1 and González-Uribe, 2013). However, whether such potential higher returns trickle down to original inventors is unclear and hard to test: VCs face a complex set of incentives, and no comprehensive data exist on return distribution between investors and founders. While alternative interpretations cannot be fully ruled out, additional results provide some supporting evidence that potential returns trickle down to founders. In particular, I show that exchanges continue to increase in situations where VCs' conflicts of interest and bargaining power over founders are plausibly low (such as when the portfolio companies involved in the exchange with the joiner are mature firms that the VCs have likely already exited because they entered the portfolio more than five years prior).

The question remains: if companies were randomly assigned across venture capital portfolios, would sharing a common VC causally facilitate exchanges of innovation resources? If so, this would constitute evidence of an additional channel through which VCs could add value to their investments (cf. Sørensen, 2007) and provide some support for the policies worldwide that encourage the

[2] This suggestion is reminiscent of theories on how intangible assets can be more valuable when they coevolve in a coordinated way with complementary assets, as seen in Rosenberg (1972).

development of venture capital markets (see Lerner, 2009). Answering this question is, however, challenging given the low feasibility of a large scale randomized trial in the venture capital setting.

Here, I exploit the staggered adoption of "prudent man rules" (PIR), which allow local pension funds to invest in venture capital across states in the US, as plausible exogenous variation in the composition of local VCs' portfolios (cf. González -Uribe, 2013).[3] I estimate that a state's PIR adoption increases the capital commitments to the local venture capital industry that are made by local state pension funds by 175 million USD (relative to pension funds located elsewhere), possibly because of home bias in state pension funds' venture capital investments (see Hochberg and Rauh, 2013).

I show that this influx in local venture capital commitments indeed changes the composition of local VCs' portfolios. PIR adoption in a state roughly doubles the mean probability that joiners first enter local VCs' portfolios, conceivably because these investors have more capital to invest, rather than because of happenstance shocks to the joiners' potential for cross-company exchanges. This influx also increases (roughly triples) relative portfolio exchanges, even in subsamples of joiners and portfolio companies that are located outside VCs' home states (and further, also outside of "coincidental states" that adopt PIR at the same time as the home states of VCs), which mitigates concerns that results are driven by the endogeneity of PIR adoption (or the potential impact of PIR adoption on other local investments not related to venture capital). I present evidence against other methodological concerns such as aggregate trends in PIR adoption, California and/or Massachusetts effects, and biases from mis-measurement in the actual implementation dates of PIR adoption across states. Under the assumption that PIR adoption in VCs' home states does not disproportionately increase relative portfolio exchanges through channels other than portfolio joining events, these additional results constitute evidence that sharing common VCs causally facilitates exchanges of innovation resources.

This paper contributes to the literature on organizational design and innovation (e.g., Seru, 2014; Branstetter and Sakakibara, 2002; Spence, 1984; Bernstein and Nadiri, 1989). As described by Teece

[3]State pension funds are regulated at the state level and were thus not covered by the Employment Retirement Income Security Act of 1979 that clarified how pension funds ran at the federal level could invest in venture capital (see Kortum and Lerner, 2000).

(2010), the most significant transformation in the organization of corporate innovation during the last five decades has been the shift away from centralized laboratories (popular in the 1950s) toward new, more decentralized models such as horizontal and vertical alliances across firms. My contribution is to show that VCs appear to select their investment portfolios based on the potential for these organizational models. Moreover, the PIR adoption results suggest that VCs can also facilitate some of these organizational models among young companies, where, absent common owners, frictions such as information asymmetries may prevent them from arising on their own.

This paper also contributes to the literature on the role of venture capital in the real economy (e.g., Kortum and Lerner, 2000; Mollica and Zingales, 2007; Hirukawa and Ueda, 2008; Popov and Rosenboom, 2009; Bernstein et al., 2016). Most related work quantifies the contribution of VCs but remains agnostic about how VCs contribute. My results point to one potential mechanism through which venture capital can influence innovation: appropriation of innovation returns inside VCs' portfolios. This mechanism is consistent with theories on how investors' portfolios provide complementary resources to support venture capital-funded firms (Hellman, 2002) and are reminiscent of prominent VCs' claims on how common cross-company collaborations are in their portfolios. Relative to the wider literature on private equity, results show that the role of this industry in the redeployment of innovative assets to efficient use extends to venture capital and is not confined to the long-documented role of buyout funds (cf., Jensen 1989; Kaplan and Stromberg, 2009).

My work is most closely related to Lindsey (2008), who shows that strategic alliances are disproportionately likely among companies sharing common VCs. Using a different methodology and sample, I show that the potential role of VCs in expanding firm boundaries is much more extensive than previously known and how it ranges from informal knowledge exchanges to more formal transfers of human and other capital resources. In addition, I offer new evidence on the timing of these exchanges, make a first pass at parsing selection from causal effects, and introduce three novel complementary mechanisms of within-portfolio exchange. My work also relates to Gompers and Xuan (2012), who explore mergers and acquisitions when the bidder and target share a common VC. There, however, the focus is on merger announcement returns and the structure of such transactions.[4]

The rest of this paper proceeds as follows. In Section 2, I describe the data. In Section 3, I explain how I measure portfolio exchanges. Section 4 describes the empirical strategy and shows that there are significant increases in relative portfolio exchanges after joiners first enter VCs' portfolios. In Section 5, I describe the PIR adoption effect on the local venture capital industry and on relative portfolio exchanges. Section 6 concludes the paper.

2. Data

2.1 Capturing data on investments by VCs

My starting point is the universe of transactions that closed between January 1976 and December 2008 and are registered in Securities Data Company's (SDC's) VentureXpert database. Before 1976, there are only a handful of publicly recorded investments by venture capital firms. While information on more recent investments is available from the same source, I consider only investments made in or before 2008, as many of my outcome variables can only be accurately measured up to that year (see Section 3). In addition, while similar information is provided by Venture Source, a unit of Dow Jones, I chose to use the SDC data, as Maats et al. (2011) and Kaplan and Lerner (2017) argue that the latter source has better coverage of investments.

I eliminate three types of investments from the data: transactions by private equity groups other than independent VCs (e.g., angel groups), transactions by venture capital firms that are not early stage investments (e.g., buyout funds), and investments by VCs in companies that were already traded in public markets before the transaction and secondary purchases. Finally, I only include investments made by US VCs in US companies.

[4] The paper also relates to Gonzalez-Uribe (2013), which shows that citations of patents increase after companies secure venture capital. I focus here only on portfolio citations, which are less than 1% of citations and explain less than 2% of the overall increase after companies secure venture capital (Gonzalez-Uribe, 2013).

For each VC and company pair, I keep track of the name of the fund through which the company first joined the VC's portfolio. In addition, I keep track of every VC's composition of its investment portfolio (i.e., all the companies that the investor has financed through its multiple funds). A company is part of a VC's investment portfolio from the first year it secures investment from such an investor until the end of the sample.

The data contain 42,670 venture capital portfolio joining events, in which 19,156 joiners enter the portfolio of one of 1,876 VCs for the first time between 1976 and 2008. All additional financing rounds between a company and an existing venture capital investor are not counted as portfolio joining events in the analysis.

2.2 Capturing data on innovating companies

I match the companies that secured venture capital to their patent records at the U.S. Patent and Trademark Office (USTPO) based on company name. To do so, I use the Harvard Business School (HBS) patent database (see Lai, D'Amour and Fleming, 2009) and the data by Kogan et al. (2017). The HBS data contain all electronic records of the USPTO for patent filings between 1976 until 2010, which have been cleaned and consolidated by HBS, including information on citations made and received by these patents, as well as the names and locations of the inventors and of the assignees. I use the data by Kogan et al. (2017) to complement information about assignee/inventor location whenever it is missing.

I restrict my sample to primary assignments of utility patents (99%) filed by U.S. companies through December 2008, because I cannot construct citation data for more recent patents given application-to-award lags at the USTPO (see Hall, Jaffe and Trajtenberg, 2001; Seru, 2014; Kogan et al., 2017). After the restrictions, the sample consists of 2,881,097 patents awarded to 1,980,696 inventors and issued to 242,767 U.S. assignees.

2.3 Combining patent and venture capital information

To combine the two databases, I strip punctuation, capitalization, and common acronyms from company names taken from VentureXpert and assignee names taken from the HBS database. I then combine the samples on the normalized company and assignee names using a fuzzy match procedure that scores potential matches based on the Levenshtein edit distance.[5] Using a random sampling procedure, I determine a score threshold such that matches with scores above the threshold are hand checked and those below the threshold are eliminated. During the manual check of the remaining matches, and whenever possible, I verify that the two companies are in the same state. In some ambiguous situations, the names are similar but not identical, or the location of the patentee differs from that given in the records of SDC. In these cases, I research the potential matches using web searches. In some cases, multiple names in either of the databases appear to match a single name in the other data set. For these, I add the observations into an aggregated entity.

After the name match, I manually go over observations that present inconsistencies in the information retrieved from the SDC and patent data sets. For example, I exclude all patents that, according to the patent data, were filed before the companies were founded (as recorded by the SDC).[6]

Patents filed by Sun Microsystems make up 9.0% of the patents filed by venture capital-backed companies. In robustness checks, I show that the results are the same if I exclude Sun Microsystems from the analysis (see Section 3.2). After these exclusions, the patent awards of no single company make up more than 5% of the data.[7] Similarly, patents filed by companies funded by the venture capital firm Kleiner Perkins Caufield & Byers constitute 15% of the data. In robustness checks, I show that the results are the same if I also exclude these companies from the analysis (see Section 3.2). Financing events by no venture capital firm or to no company constitute more than 5% of the sample [New Enterprise Associates Inc. and Applied Micros Circuits Corporation are, respectively, the venture capital firm and company with the next largest number of financing events, 247 (2%) and 14 (0.12%)].

[5] The Levenshtein edit distance is a measure of the degree of proximity between two strings and corresponds to the number of substitutions, deletions, or insertions needed to transform one string into the other one (and vice versa).

[6] Further, I also exclude companies founded before 1976 and companies that filed innovations or were founded more than ten years before they secured their first VC investment. For example, I exclude all patents assigned to SmithKline Beckman Corporation, which was founded in 1830. Although investments in this company pass all the restriction filters imposed before the match, this company does not correspond to the typical VC investment. Not only had the company been established for more than 100 years before securing VC, but the investment was by Faneuil Hall Associates, a family investment firm that was classified by SDC as a venture capital firm.

[7] Other important companies in the sample in terms of the number of patents include 3Com Corporation (1.3%), Altera Corporation (1.5%), Applied Materials Inc. (4.1%), Compaq Computer Corporation (1.8%), Cypress Semiconductor (1.5%), Genentech Inc. (1.5%), SciMed Life Systems (1.6%), VLSI Technology Inc. (1.0%), and Xilinx Inc. (1.8%).

2.4 *Analysis sample*

The final sample includes information for 3,960 joiners that filed 74,771 patents (approximately 2.5% of all patent awards) and first entered the portfolio of one of 1,265 VCs during 1976-2008. The data include 11,815 portfolio joining events (approximately 28% of joining events in the SDC data). The small size of the matched sample relative to the universe of patenting assignees is consistent with the relatively small size of the venture capital industry. The modest sample size, relative to the universe of joining events, is consistent with the prevalence of venture capital investments in industries where intellectual property is not necessarily protected using patents (e.g., internet, media, and software companies) and with the large attrition of companies in the SDC files (i.e., one-third of the companies that secure VC financing are liquidated, many of them before the company files a patent).

I structure the data in “portfolio joining event time” for every joiner and VC pair in the sample. I collect information on exchanges across the joiner and the portfolio companies of the VC five years before and six years after the joining event. For some of the joining events early (late) in the sample I can only collect information for a window of less than five years before (six years after) the investment. In robustness checks, I show that the results are quantitatively similar if I restrict the data to joining events for which information for the full 11-year window is available (see Section 4.2).

Table 1 presents the composition of the sample and summary statistics. The first five columns in Panel A show the distribution of portfolio joining events over time by type of investment: total, seed, early stage, expansion, and later stage. The last two columns in Panel A show the distribution over time of patent applications and grants.

Panel A in Table 1 shows that the distribution of patent applications and portfolio joining events mimics the increase and decline of the venture capital industry throughout the boom and bust of the dot-com crisis, particularly early stage joining events. The distribution of grants reflects the lags in patent awards by the USPTO.

Panel B in Table 1 shows the distribution of the sample across companies’ and VCs’ home states. Not surprisingly, the sample is concentrated in California (56% of patents, 47% of companies, and 33%

of VCs), where most VC activity takes place in the US. In robustness checks I show that the results are not driven by potential California effects (see Sections 4.2 and 5.4). Panel C shows the distribution of patents in the sample across two-digit technology classes. The most popular technology classes include Computer Hardware and Software (17%), Communications (11%), Semiconductor Devices (10%), and Medical Instruments (9%). The importance of these technology classes in the sample reflects the industry distribution of VC investments described in Panel D, which is concentrated in medical health (18%), semiconductors (17%), computer software (16%), and communications (11%).

3. Measuring cross-company exchanges of innovation resources

Because exchanges of innovation resources between companies are not observable, I construct several proxies based on company interactions related to the distribution and promotion of innovations. Several such proxies have been associated by prior work to the successful commercialization of inventions, such as patent citations, patent reassignments, worker exchanges, strategic alliances, and mergers and acquisitions.

Patent citations are the standard metric in the innovation literature to measure knowledge exchanges (Jaffe, Trajtenberg, and Henderson, 1993; Hall, Jaffe, and Trajtenberg, 2005; Kogan et al., 2017). These citations serve the important legal function of limiting the innovation protected by the patent document.[8] While patent citations are useful in that they allow for a paper trail between innovations, the downside is that parties other than the inventors may add citations, and hence some citations may not necessarily reflect actual knowledge flows between the cited and citing parties (Thompson and Fox-Kean, 2005; Roach and Cohen, 2010). For example, it is possible that VCs encourage citations across companies in their investment portfolio for legal reasons, such as building patent thickets that may restrict the access of other unrelated parties to their knowledge. These strategic citations may also be consistent with cross-company exchanges that can increase profits from inventions. The difference is that they would not correspond to knowledge flows but rather to exchanges of intellectual property protection. Using

[8] Arguably, this legal function creates strong incentives for inventors to get these citations right. As Jaffe, Trajtenberg, and Henderson (1993) put it, including extraneous citations is “leaving money on the table.” Likewise, deliberately excluding citations can expose the company to costly sanctions by the regulator or infringement lawsuits (Branstetter, 2006).

information from the HBS patent data set and from Kogan et al. (2017), I construct three proxies of exchanges of innovation resources based on patent citation data: Citations received, Citations made, and Overall citations. These proxies measure over time, respectively, citations from the portfolio companies to the patents of the new joiner, citations from the joiner to the patents of other portfolio companies, and the combination of both of these types of citations. Given the lag between application grants and applications, I only consider patents filed by 2008, so as to have at least two years of citation data (the last year of filings in the patent data is 2010; see Section 2.2).

Patent reassignments are transfers of intellectual property between patent assignees and third parties. They have been used in several papers as measures of ownership transfer of innovations between companies (Akcigit, Celik, and Greenwood, 2016; Galasso, Schankermann, and Serrano, 2013; Hochberg, Serrano, and Ziedonis, 2018; Serrano, 2010). I focus here on reassignments to other innovative companies given the investment profile of venture capital firms. I note however, that other important patent reassignments include collateral pledges to financial institutions (see Mann, 2018). Based on data from the USTPO Bulk Downloads at Google, I construct three proxies of exchanges of innovation resources using patent reassignments: Patents sold, Patents bought, and Patent sales.[9] The first (second) proxy measures over time the patents bought by (sold to) joiners from (by) other portfolio companies. The third proxy combines the first two measures of patent reassignments.

Cross-company worker mobility mediates exchanges of innovation resources, such as knowledge flows, between firms (Almeida and Kogut, 1999; Agrawal, Cockburn, and McHale, 2006; Azoulay, Zivin, and Sampat, 2012; Kaiser, Kongsted, and Rønde, 2015; Fallick, Fleischmann, and Rebitzer, 2006). This type of exchange can be especially relevant in the venture capital context, as VCs are also known to help companies hire (cf. Hellman and Puri, 2002). Worker mobility between two companies is inferred here mostly from the inventor files of the patent data because comprehensive information on the workers of venture capital-backed companies is not publicly available.[10] I define an inventor as

[9] See: https://www.google.com/googlebooks/uspto-patents-assignments.html
[10] In complementary analysis, I also use information on company executives available at SDC; see Section 4.4 for more details.

moving from company A to company B at time *t*, if at time *t* the inventor assigns a patent to company B, and at any year prior to *t* the inventor assigned a patent to company A. I construct three proxies of exchanges of innovation resources using the HBS inventor data: Inventor emigrates, Inventor immigrants, and Inventor exchanges. The first (second) proxy measures over time the number of inventors that moved from the joiner (any portfolio company) to any of the portfolio companies (the new joiner). The third proxy combines the first two measures. I note that these proxies are not meant to capture, and do not necessarily capture, violations of noncompete agreements, which are common in employment contracts (Marx, 2013; see also discussions in Sections 5.3 and 5.4). Rather, these measures are more likely to measure the legal turnover of inventors across firms.

I also consider several types of business integration between joiners and portfolio companies, including alliances as well as mergers and acquisitions. Alliances have been used as measures of exchanges of innovation resources between firms (Mowery, Oxley, and Silverman, 1996; Stuart, 2000; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), particularly venture capital-backed firms (Lindsey, 2008), while mergers and acquisitions are a standard measure of firm integration in the finance literature (Seru, 2014). I construct two final proxies of exchanges of innovation resources based on these additional data: alliances and mergers and acquisitions. Each proxy equals one after the joiner and at least one of the portfolio companies enter an alliance or merge (get acquired or are acquired), respectively. I manually match the companies that secured venture capital to their alliances and merger and acquisition activity based on company name. To do so, I employ information from SDC Platinum at Thomson-Reuters.[11]

Table 2 shows summary statistics of the different proxies of exchanges of innovation resources between joiners and portfolio companies in the sample. I refer to these exchanges as portfolio exchanges throughout.

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[11] The data on alliances include 128,770 alliances between US-based companies for the 1972-2016 period. There are a total of 17,366 alliances between innovating companies and 5,485 (761) in which at least one (both) of the innovating companies is VC-backed. The data on mergers and acquisitions include 324,762 mergers and acquisitions between US-based companies for the 1972-2016 period. There are a total of 95,341 mergers and acquisitions between innovating companies and 38,563 (6,891) in which at least one (both) of the innovating companies is VC-backed.

3.1 Patterns in portfolio exchanges between joiners and other portfolio companies

Fig. 1 plots the average portfolio exchanges between joiners and portfolio companies for the different proxies against joining event time. The solid (dotted) line plots the estimated coefficients (95th confidence intervals) of the $\beta_k s$ in the following equation:

$$y_{ijt} = \alpha_{ij} + \sum_{k=-5}^{5} \beta_k Event_{ijt+k} + \gamma_t + \varepsilon_{ijt}, \quad (1)$$

where y_{ijt} is any measure of portfolio exchanges between joiner *i* and portfolio companies of VC *j* at time *t,* and the $Event_{ijt+k}s$ are event-time dummies that light up k years before/after the joiner first joins the VC's portfolio. Fixed effects for every pair of joiner and VC, α_{ij}, absorb any time-invariant complementarities between joiners and other portfolio companies. Calendar year fixed effects, γ_t, control for aggregate trends in the different measures of portfolio exchange.

The series of coefficients β_k are the main estimates of interest. For $k > 0$, β_k is an estimate of the change in portfolio exchanges *k* years after the joining event between portfolio companies and joiners, relative to all other portfolio exchanges for joiners in the sample that did not enter the portfolio of a VC *k* periods ago but did so before or will do so after. Similarly, for $k < 0$, β_k is an estimate of the change in portfolio exchanges k years before the financing event. The β_k coefficients are normalized relative to the year before the joining event ($k = -1$), which is set to zero. Standard errors are clustered at the joiner and VC pair level to adjust for heteroskedasticity and within-pair correlation over time.

Fig. 1 shows that after joiners enter VCs' portfolios for the first time, portfolio exchanges between them and other companies in the portfolio increase. For example, Panel A shows an increase in Citations received after the joiner enters the portfolio, while no trend exists prior to the joining event. The rest of the panels in the figure plot portfolio exchanges between joiners and portfolio companies against joining event time for the different proxies and show a similar increasing pattern.

The patterns in portfolio exchanges exhibited in Fig. 1 are consistent with the prevalence of exchanges of innovation resources inside venture capital portfolios. Other potential explanations naturally exist. For example, the patterns can also reflect trends in the size of venture capital portfolios and joiners. Given that VCs often specialize their investments, the patterns may also reflect potential industry, scale, technology, and location clustering effects.

To control for potential aggregate trends and clustering effects, I adjust all metrics of portfolio exchanges using data on the different proxies of exchanges of innovation resources between joiners and matched portfolio companies. For every company in the portfolio of a VC, I select an observationally equivalent match from the universe of patenting companies in the US that did not secure venture capital over the sample period. In particular, portfolio companies and their respective matches are located in the same state and have the same patent-production scale (i.e., number of patents), technological base (i.e., distribution across two-digit technology classes of citations made to prior innovations), and technological focus (i.e., the three-digit technology class mode of patents).[12] Because venture capital-funded companies are likely to have different growth paths than non-venture-backed companies, the matches are recalibrated every year.[13] Online Appendix 2 has a detailed explanation of the matching procedure and discusses matching statistics. Using these matched portfolio companies, I then estimate relative portfolio exchange measures for all the outcome variables included in the analysis. For each original measure of portfolio exchanges, the relative version subtracts (from the original) the respective exchanges between joiners and matched nonportfolio companies. To distinguish between the different types of exchange measures, I identify the matched measures with the prefix "matched," and the relative measures with the prefix "relative." Table 2 reports summary statistics for the relative and matched outcome variables.

Fig. 2 shows that potential aggregate trends or clustering effects cannot explain the increase in portfolio exchanges after the portfolio joining event. Following the same structure as Fig. 1, Fig. 2 plots relative portfolio exchanges between joiners and portfolio companies against joining event time for the

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[12] In Online Appendix 4, I show that results are quantitatively similar when I use alternative matching methodologies based on the amount of venture funds raised, company, age, location, and technology (see also Section 4.2).

[13] In unreported results, I check whether the results are the qualitatively the same if I rely instead on a single match across the sample for each portfolio company. I present the results using the annual matches because the matching statistics are significantly better, as discussed in more detail in Online Appendix 2.

different proxies. The increasing pattern post-joining is still evident for the relative measures. For most of the relative exchange metrics, there is a clear mean shift after joiners enter the portfolio (see Panels A-I). For Relative alliances and Relative mergers and acquisitions, there is a sharp trend break after joiners enter the portfolio (see Panels J and K, respectively). The patterns suggest that more contractually difficult arrangements across joiners and portfolio companies (such as integration) are only established with time, after the joiners settle in the portfolio.

Fig. 2 also shows that the increase in relative portfolio exchanges holds for both exchanges financed by joiners and those financed by the other companies in the VC's portfolio. After joiners first enter a VC's portfolio, portfolio companies are relatively more likely to cite (Panel A) and purchase (Panel D) joiners' patents as well as hire joiners' inventors (Panel G). These results suggest that financing effects where the increase in relative portfolio exchanges is due to the cash infusions of joiners can only partially explain the results, as portfolio companies do not generally secure financing at the same time as the new joiner. Other potential explanations include the mitigation of contracting complexities, which are also prevalent among young companies, inside VC portfolios.

Fig. 2 also shows evidence of anticipation effects (that is, evidence of increasing relative portfolio exchanges before the joiner first enters the portfolio), such as Relative citations made (Panel B) and Relative inventor immigrants (Panel H). These patterns suggest that portfolio exchanges can be used as a basis for selecting investment portfolios by VCs.[14] For some of the metrics, the trend plateaus or reverts after a couple of years.[15] The timing of this plateau is likely explained by the exit of the VC from the company (cf. Lindsey, 2008).

4. Empirical strategy

[14] Unreported results suggest that VCs also use information on portfolio exchanges to select possible syndication partners. I find that the prefunding patterns in Figs. 1 and 2 are more pronounced for the later rounds when the investment syndicate increases than for the earlier rounds. This additional result is broadly consistent with the work of Hochberg, Lindsey, and Westerfield (2015) on the importance of resource accumulation in the formation of venture capital co-investment networks.

[15] For example, the plots for Relative inventor emigrates (Panel G) and Relative inventor immigrants (Panel H), respectively

I summarize the results of the portfolio joining event study analysis of Section 3.1 in Table 3. I report results from a more parsimonious model than Eq. (1):

$$y_{ijt} = \alpha_{ij} + \beta Post_{ijt} + \delta Post_{ijt} \times \tau + \gamma_t + \varepsilon_{ijt}, \qquad (2)$$

where $Post_{ijt}$ is a variable that equals one after joiner i enters the portfolio of VC j for the first time. The term $Post_{ijt} \times \tau$ is the interaction between $Post_{ijt}$ and the number of years since the time of the joining event (τ). This interaction term will be equal to zero in the years before the joiner enters the portfolio and start at one in the year after the joining event.

The specification in Eq. (2) allows for both a mean shift (β) and a trend break (δ) after the joining event, which captures the dynamics of joining venture capital portfolios more flexibly. The coefficient of interest, β (δ), measures the change in the mean (slope) outcome of interest before and after the portfolio joining event. These changes are relative to all other joiners that do not join a new portfolio in that year (but have either already entered a new portfolio or will join a new portfolio in the future).

I do not control for any time-varying variables at the level of the new joiner, portfolio, or pair, as most of these are outcomes of the joining event. Therefore, I cannot separate the effect of entering the portfolio from the effect of other changes that occur at the same time as the joining event but are not related to the event. In all regressions, standard errors are clustered at the joiner and VC pair level to adjust for heteroskedasticity and within-pair correlation over time. The results are quantitatively similar with other levels of clustering (see Section 4.2).

4.1 Main results

Table 3 confirms the patterns in Figs. 1 and 2. After a joiner first enters the portfolio of a VC, there is a positive and significant mean shift in portfolio exchanges (Panel A) as well as in relative portfolio exchanges (Panels B) between the joiner and other companies in the VC's portfolio. On average, the different types of portfolio exchanges increase by 60% (over the sample mean) relative to nonportfolio exchanges.[16] The largest mean shift is for Relative inventor exchanges, which increase by 0.012

[16] For example, the estimated number of additional portfolio citations received by new joiners within five years of the joining event is 0.47 (0.02+0.03×1+…+0.03×5; see Panel A in Table 3).

(Column 9, Panel B), corresponding to a 120% increase over the sample mean (0.01; see Table 2). The smallest significant mean shift is for Relative patents sold (Column 4, Panel B), which increase by 0.004, representing a 40% growth over the unconditional mean (0.01; Table 2). Online Appendix 3 shows that the increase in relative portfolio exchanges is similar on both the coasts, where VC funding is common, as well as in the rest of the US.

The last two columns in Panel B of Table 3 show a trend break of 0.001 in both Relative alliances, and Relative mergers and acquisitions, even though there is no mean shift. This trend break is economically significant; it respectively corresponds to a 100% and 50% increase per post-event year over the sample mean (0.001 and 0.002; Table 2). Evidence in support of a trend break but not in support of a mean shift in Relative alliances simultaneously confirms Lindsey's (2008) "alliance mechanism" (using a different methodology and sample) and suggests that this mechanism of resource exchange is not the only one at work within venture capital portfolios (as there is evidence of a mean shift for all other measures except mergers and acquisitions). The results in Online Appendix 3 confirm this suggestion by showing that the increase in portfolio exchanges holds after I exclude all joiners with within-portfolio alliances from the analysis. I return to a discussion of potential mechanisms in Section 4.4.

4.2 Robustness checks

Results from several robustness checks are summarized in the Online Appendix. Online Appendix 3 shows the findings are not driven by state, firm, or company-level influential observations; most results (20 out of 22) hold after I exclude observations from the states of California and/or Massachusetts and from the firms Kleiner Perkins and Sun Microsystems. The results are also robust to excluding all joiner and VC pairs for which I cannot construct the full financing event 11-year window (see Section 2.4).

Online Appendix 3 also shows that differential trends across industries or states do not drive the results, which continue to hold after I include fixed effects at the level of industry by year, joiner state by year, and VC state by year. They also hold for different levels of clustering at the VC level, joiner level, or at both the VC and joiner levels. Concerns of serially correlated outcomes are also mitigated in the Online Appendix, where I show that results are quantitatively similar after I collapse the time series variation to a two-period pair panel (and include fixed effects for every joiner and VC pair in the estimation). Because joining events occur at different years across joiner and VC pairs, I collapse the data by using pairwise residuals from regressing y_{ijt} (i.e., the proxy of exchanges of innovation resources) on year dummies and aggregating those from years before and after the joining event into the pre- and post- periods for every joiner and VC pair in the data (see Bertrand, Duflo, and Mullainathan, 2004).

In Online Appendix 3, I also show that the results are not driven by a mechanical increase in VC portfolio size over time nor by spurious time trends. I summarize results from 1,000 placebo tests where I randomly pick the years of joining events for the pairs in the sample. Nonrejection rates are close to (and often below) 5% for all measures of portfolio exchanges, as would be expected from randomly choosing the joining events.

Finally, Online Appendix 4 shows that the results are not driven by differences between companies in and out of the venture capital industry. The findings are quantitatively similar under alternative matching methodologies based on the amounts of venture capital raised as well as on company age, location, and technology.

4.3 Heterogeneity

Tables 4 and 5 report the regression results from several cuts of the sample. Consistent with VCs potentially facilitating portfolio exchanges, Panels A and B in Table 4 show that the relative increase in portfolio exchanges appears strongest (for most proxies) for joiners and pairs where the expropriation risks and information asymmetries are largest. Most notably, the increase is stronger for joining companies that are more likely to have uncertain products and technologies, such as younger firms (Panel A) or those in an early stage of development (Panel B). Younger firms are those that are below the median company age of two years at the time of financing. Company age is measured relative to founding age. Early stage firms are those whose first investment by a VC was secured either at seed or early stage according to the SDC files.

Also consistent with VCs facilitating exchanges of innovation resources, Panel A in Table 5 shows that the increase in portfolio exchanges holds in situations where cross-company exchanges are likely fraught with contracting complexities. Most notably, and consistent with Lindsey (2008), the increase holds between industry competitors (i.e., joiners and portfolio companies that have the same SDC industry classification).[17]

Panel D in Table 4 shows that the increase in relative portfolio exchanges is, on average, stronger and materializes faster (i.e., there is a significant mean shift after joiners enter the portfolio) for more experienced VCs, as measured by the number of prior investments made by the VC, following Lindsey (2008). For younger VCs, the effect is instead more gradual; columns 1, 3, 4, 5, 6, 10, and 11 show a positive and significant trend break (but no evidence of a mean shift) after joining young VCs' portfolios. In unreported regressions, I confirm that the differences across senior and junior VCs are not driven by differences in portfolio size across investors of different ages. These differences also hold for "first rounds" where companies secure venture capital (from any investor) for the first time and appear stronger for later (i.e., not the first) investment rounds. A VC is defined as young if its age is below the median investor age of six years at the time of the investment, as measured relative to the first time in the SDC data that the VC makes an investment.

Further, consistent with how competition for VCs' resources may also prevent cross-company exchanges, Panel B in Table 5 shows the increase in relative exchanges is often most pronounced between joiners and other companies in the portfolio of the VC that are not in direct competition for the VC's resources because they were financed by a different fund. For joiners and portfolio companies financed by the same fund of the VC, only relative portfolio exchanges related to patent reassignments (columns 4-6, Panel B) are more likely to increase after the portfolio joining event.

[17] In unreported exercises, I show that the results are similar across new joiners of "generalist" and "specialist" VCs. I code a VC with a minimum of five investments as specialist (generalist) if 90% of its investments over the previous five years are (not) focused on one SDC sector, following Hochberg, Mazzeo, and McDevitt (2015).

The main implication of results is that exchanges of innovation resources appear prevalent in venture capital portfolios. Since the successful commercialization of inventions typically requires firms to combine their inventions with other complementary resources that they do not own or develop, my preferred interpretation of the results is that returns to innovation are higher when inventions are developed inside venture capital portfolios. This interpretation is supported by prior literature showing positive links between cross-company exchanges and value, such as studies showing how resource exchanges across firms are met, on average, with positive reactions in the public equity markets (e.g., Hall, Jaffe, and Trajtenberg, 2005, for patent citations; Denis and Denis, 1995, for CEO turnover; Chan et al., 1997, for alliances; and Kaplan, 2006 for mergers and acquisitions). However, I cannot fully rule out that in the venture capital context, higher innovation rents do not trickle down to inventors: VCs are subject to a complex set of incentives (e.g., Hellman, 2002) and typically hold large bargaining power over founders. Empirically, the related evidence is mixed (cf., Masulis and Nahata, 2011; Lindsey, 2008), and scarce, because innovation returns are particularly hard to measure for the private firms that are the usual targets of VCs. Although alternative interpretations cannot be fully ruled out, additional results provide supporting evidence that potential returns trickle down to founders. In particular, this interpretation is supported by results showing that portfolio exchanges also increase in situations where VCs' conflicts of interest are potentially low, and where VCs have little bargaining power over the portfolio companies involved in the exchange with the joiner, such as in mature firms that entered the portfolio more than five years prior and that VCs are likely to have already exited (see Online Appendix 3).

4.4 Mechanisms

Tables 6 and 7 summarize the results from a battery of tests, which, taken at face value, support three novel mechanisms of exchanges of innovation resources inside venture capital portfolios.

The first mechanism is spawning, by which I mean instances where entrepreneurs move on to start new companies also financed by the same VCs. In support of this mechanism, Panel A in Table 6 starts by showing that inventors that emigrate from the joiner towards the VC's portfolio appear to go mostly toward future rather than to incumbent portfolio companies (compare columns 4 and 7 in Panel A). This temporal emigration pattern of inventors is as expected with spawning; the idea is that entrepreneurs leave to start new companies that have not been founded at the time of the joining event. I classify firms into incumbent and future portfolio companies according to whether they already exist in the portfolio during the new joiner's joining event. Inventor exchanges are then categorized (and denoted by a corresponding suffix) into future or incumbent according to the type of portfolio company they move to or from.

Because many founders do not file patents, but most should hold executive positions in the firm, I provide additional and arguably more direct evidence of the spawning mechanism by investigating the emigration patterns of the company executives reported in SDC.[18] Panel B in Table 6 shows two striking results in support of the spawning mechanism. First, executive exchanges, as measured by the movement of executives across companies, are also prevalent inside VC portfolios: there is a 153% increase in executive exchanges (to and from joiners and the VC's portfolio) after joiners enter the portfolio (0.020 relative to the unconditional mean of 0.013; see column 3 in Panel B). Second, company executives have the same temporal pattern of emigration as inventors: most executives tend to leave for future, rather than incumbent, portfolio companies (compare columns 4 and 7 in Panel B).[19]

The second mechanism of exchanges of innovation resources inside venture capital portfolios that finds support in the data is carve-outs, i.e., instances where entrepreneurs divest some of their innovation units inside the portfolio. The increase in Relative mergers and acquisitions shown in Table 3 (column 11, Panel B) provides the first piece of evidence consistent with this mechanism. Because carve-outs are likely to involve the simultaneous exit of several workers (say, all inventors in one same business unit), rather than the isolated transfer of individual workers, I move on to explore the prevalence of, and

[18] I retrieve data on executives from SDC and define an executive as moving from company A to company B at time *t*, if at time *t* the individual appears as an executive of company B, and at any year prior to *t* the individual appeared as an executive of company A. The variable Executive emigrates (Executive immigrants) measures the number of executives that moved from the joiner (any portfolio company) to any of the portfolio companies (the new joiner) over time. Executive exchanges measure all executive movements.

[19] The analysis of executives has some limitations. First, I only capture executive changes if companies raise rounds of financing. If they do not, they will not appear in the SDC sample. Thus, as with measures of inventor exchanges, my executive metrics likely underestimate executive exchanges. Second, I cannot construct measures of relative executive exchanges (which control for technological clustering in portfolios) because there is no information on the executives of nonportfolio companies.

circumstances surrounding, grouped departures. The results in Table 7 provide further support for carve-outs: Panel A shows that the bulk of inventor emigrations constitute grouped departures (compare columns 3 and 5); that is, instances in which more than one inventor (i.e., a team of inventors) emigrates. More importantly, Panel B shows that 7% (3%) of such grouped departures occur within four years of a within-portfolio merger or acquisition of the joiner by an incumbent (future) portfolio company. Group departures are hand classified into seven categories of corporate events by comparing the timing of the emigration and the timing of such corporate events.[20] Finally, I make further use of the executives' data to provide additional evidence in support of carve-outs. The results in Panel C of Table 6 show that almost 10% of inventor exchanges coincide with the executives of the joiner also leaving the firm (column 6).[21] This coincidence is consistent with carve-outs, as I expect both scientists and managers to exit firms in tandem when companies divest some of their innovation units.

The final mechanism of exchange of innovation resources inside venture capital portfolios supported by the data is recycling, whereby the assets of restructuring portfolio companies are absorbed by other portfolio firms. Panel B in Table 7 shows that 31% of grouped departures from joiners toward portfolio companies can be traced to a restructuring event of the new joiner, such as a merger or acquisition (with a company outside of the portfolio of the VC, 22%), an initial public offering (2%), or a more informal reorganization (such as the hiring of new CEOs, 7%). Results in the panel also show that 3% of grouped departures absorbed in the portfolio follow a liquidation event of the new joiner.

Overall, the preponderance of evidence in Tables 6 and 7 supports the mechanisms of spawning, carve-outs, and recycling, although I cannot directly test any of these channels due to data limitations (e.g., there are no public records on divesting discussions by VCs and entrepreneurs). These mechanisms are also broadly consistent with prior work and with anecdotal evidence, but this analysis is, to my

[20] The seven categories of corporate events are: merger or acquisition by a company outside the VC portfolio, merger or acquisition by an incumbent portfolio company, merger or acquisition by a future portfolio company, IPO, liquidation, restructuring, and founding. The class reorganization includes several types of corporate events including: the hiring of new CEOs, securing investment from government, and opening a foreign subsidiary. An inventor emigration is classified as a respective corporate event if it occurs within four years of the event. An emigration event is unclassifiable if it does not occur within four years of the six corporate events considered.

[21] For this complementary test, I combine information on inventors and executives and construct measures of conditional inventor exchanges (i.e., conditional on simultaneous executive movements).

knowledge, their first collective quantitative evidence. For example, spawning echoes the serial entrepreneur phenomenon studied elsewhere (e.g., Gompers et al., 2010). The novelty here lies in showing that the recurring pattern is also found in the relations between entrepreneurs and the same investors rather than just in the unilateral founding decisions of entrepreneurs. While other work examines the repeated relationships between VCs and serial founders (e.g., Bengtsson, 2013), evidence on how these repeated relations also extend to inventors is new. Similarly, carve-outs are consistent with the notion that VCs help companies recruit key personnel (e.g., Hellman and Puri, 2002; Kaplan and Stromberg, 2001), and support the bridge-building role of VCs in mergers and acquisitions as shown by Gompers and Xuan (2012). The focus on bulk hiring of inventors is new here, and is reminiscent of the "acqui-hiring" phenomenon described by the popular press. Finally, recycling is consistent with the well-documented fact that VCs play a major role in exits, such as structuring mergers, acquisitions, initial public offerings, and liquidations (e.g., Sahlman, 1990). The evidence on the reuse of human capital assets inside the portfolio is novel and points to one specific role for VCs: strategic management of residual assets in restructurings.

5. Exploiting the adoption of PIR across states as an exogenous determinant of VCs' portfolios

The question remains: if companies were randomly assigned across VCs' portfolios, would sharing a common VC facilitate exchanges of innovation resources? Because a large scale randomized trial is unfeasible in this setting, in this section, I exploit regulatory changes to the investment policy of state pension funds (namely, the adoption of PIR) as plausible exogenous variation in the composition of VCs' portfolios. I begin by providing a background of the PIR. Then, I show that PIR adoption in a VC's home state predicts the timing of when joiners enter VCs' portfolios for the first time as well as the prevalence of portfolio exchanges between joiners and other portfolio companies. I conclude by presenting several robustness checks and discussing the interpretation of the results.

5.1 Institutional setting: adoption of prudent investor rules across states

State pension funds are among the most important limited partners in the venture capital industry. In 2011, they accounted for 28% of new funds committed to venture capital, almost twice the 13%

accounted for by the industry's second most important capital provider, fund of fund managers.[22] Prior work shows that these funds have a substantial home state bias in their private equity investments (see Hochberg and Rauh, 2013). The likely cause of this home state bias is local development policies, in the form of economically targeted investments, to which state pension funds are typically subject. For example, state pension funds are often required to invest in companies and industries located within the state's borders as a way of promoting local employment (Brown, Pollet, and Weisbener, 2012).[23]

State pension funds are governed at the local level. Their significant participation as limited partners of venture capital firms can be traced back to state-level regulatory changes on such funds' admissible investments. In particular, this participation can be linked to the adoption of prudent investor rules (PIR) that allowed state pension funds, which were not covered in the Employee Retirement Income Security Act (ERISA) clarification of 1979, to invest in venture capital. State-level PIR adoption was prompted by the 1994 Uniform Prudent Investor Act (UPIA) of the Uniform Law Commission. Similarly to ERISA, UPIA requires trustees to become devotees of "modern portfolio theory" and to invest as a prudent investor would invest by "considering the purposes, terms, distribution requirements, and other circumstances of the trust" while using "reasonable care, skill, and caution."

State-level adoption of PIR through UPIA began during the early 1990s, when state pension funds accounted for only 4% of funds committed to VC.[24] Today, the majority of US states (46) have adopted PIR by enacting UPIA. Adoption was staggered across states, as shown in Fig. 3. Information about UPIA adoption is from Uniform Laws Annotated, published by Thompson-Reuters and summarized in Online Appendix 5. I consider two different proxies for the date of PIR adoption in each state: PIR enactment (i.e., the date the UPIA legislation was signed into law in the state) and PIR implementation (i.e., the effective date of the UPIA enactment). Online Appendix 5 shows PIR implementation lags behind PIR enactment in 15 out 46 states. The average lag is 0.37 years among the 46 states and 1.13

[22] Source: author's calculations using Preqin data for 2011.
[23] Brown, Pollet, and Weisbener (2012) report, "Overall, we find that the state-managed equity portfolios hold a broadly diversified portfolio of stocks. Relative to the value weighted index of all US equities, these state managed plans overweight large (i.e., S&P 500) stocks. […] However, we also find strong evidence that these plans overweight the stocks of companies that are headquartered in the state."
[24] Source: author's calculations using Preqin data for 2011.

years among the states where there is a lag. Among the early adopters were Illinois, New York, and California, which adopted PIR via UPIA enactment in 1992, 1994, and 1995, respectively. The latest adopter of PIR via UPIA enactment was Montana in 2013.

Similar to how ERISA increased funding for the US venture capital industry, state-level PIR adoption increased local venture capital firms' funding sources. Following states' PIR adoption via UPIA enactment (implementation), capital commitments to local venture capital firms by state pension funds increased by an average of 175 (187) million USD relative to pension funds located in other states. The increase was economically significant: it corresponded to a 54% (29%) relative increase over average nominal (real) capital commitments prior to PIR adoption via UPIA enactment. This increase was not exclusively driven by California and reflected a general shift in the investment policy of state pension funds toward local private equity (including buyout funds). To produce these estimates, I compare changes in capital commitments to local venture capital firms by local state pension funds (which were affected by the PIR adoption) relative to those from pension funds located elsewhere (which were not affected by the PIR adoption) after a state's PIR adoption, using a triple difference–in–differences methodology. In Online Appendix 6, I explain in detail the data sources and methodology used to produce these estimates and summarize the results.

5.2 PIR adoption and the timing when joiners enter VC portfolios

The evidence in Section 5.1 suggests that a state's adoption of PIR provides a source of plausible exogenous variation in the portfolio composition of local VCs. PIR adoption allows local VCs to make some investments they otherwise would not have made by increasing their access to funding capital from local state pension funds.

Consistent with states' PIR adoption affecting the composition of local VCs' portfolios, I show in Fig. 4 that joiners are twice as likely to enter VCs' portfolios for the first time after PIR adoption in VCs' home states. Fig. 4 plots average Post for joiners and VC pairs in the sample against PIR event time dummies that indicate for each pair the year relative to PIR adoption in the VC's home state. In the figure, Panel A (B) dates PIR adoption according to UPIA enactment (implementation); see Section

4.1 and Appendix 5. Both panels in the Figure show that roughly ten years prior to PIR adoption, a slight negative trend exists in average Post. After PIR adoption, however, the trend changes, with average Post beginning to increase one year after PIR adoption, and continuing to do so for roughly 12 years. The figure also shows a slight upward trend in average Post throughout the entire PIR adoption event time (see discussion in Section 5.4). To construct this plot, I organize the (joiner VC) pair panel data in "PIR event time," where the event is the PIR adoption date in the VC's home state. I then regress Post against PIR event time dummies and cluster standard errors at the level of the VC's home state. I include the VC's home state fixed effects in the regression. The solid (dotted) line plots the estimated coefficients (95th confidence interval) of the PIR event time dummies. The coefficients are normalized relative to the year before PIR adoption, which is set to zero. Joiner and VC pairs where the VC is located in a state with no PIR adoption in the sample period are excluded from the plots by design.

I summarize the results of the PIR event study plots in Fig. 4 by estimating the following equation:

$$Post_{ijt} = \alpha_{ij} + \beta PIR_{jt} + \varepsilon_{ijt}, \qquad (3)$$

where PIR_{jt}, is an indicator variable that equals one after the state of the VC investor j adopts PIR on a two-period panel data set (i.e., a pre- and post-PIR adoption period) of the joiner and VC pairs in the sample for which the home state of the VC adopts PIR within the sample period.[25] I collapse the time series information for each joiner and VC pair to control for potential trends in PIR event time and serial correlation of standard errors, which are common in difference-in-differences exercises exploiting the staggered adoption of regulations across states (see Bertrand, Duflo, and Mullainathan, 2004). Because the timing of PIR adoption across states is not the same, but is instead staggered, to collapse the time series information, I use residuals from regressing $Post_{ijt}$, on VC home state fixed effects, year dummies, and differential trends across the home states of the VCs. For every joiner and VC pair in the data, the residuals from the years before and after PIR adoption in the VC's home state are aggregated, respectively, into the pre- and post-adoption period observations. Eq. (3) is estimated by

[25] The states that adopted PIR out of the sample period are Montana, Vermont, Delaware, Kentucky, Louisiana, and Maryland.

using ordinary least squares (OLS), the aggregate residuals as dependent variable, and clustering standard errors at the level of the home state of the VC.

Column 1 in Panel A of Table 8 shows that the increasing pattern in $Post_{ijt}$ after PIR adoption that is shown in Fig. 4 is statistically and economically significant. Joiners are 101% more likely (relative to the sample mean) to enter the VC's portfolio after PIR adoption in the VC's home state (0.618 relative to 0.61; see Table 2).

5.3 PIR adoption in VCs' home state and portfolio exchanges

Columns 2-12 in Panel A of Table 8 show that relative portfolio exchanges (between joiners and other companies in VCs' portfolios) also increase (namely, they triple) after PIR adoption in the VCs' home state. The panel presents reduced form estimates of portfolio exchanges on PIR adoption from estimating Eq. (3) using the aggregate residuals of the different measures of portfolio exchanges, rather than the aggregate residuals of Post, as dependent variables.[26] Across the columns, the point estimates are positive and statistically significant, except for Relative inventor immigrants in Column 9. Relative to the sample means, these estimates imply an average increase of 204% in relative portfolio exchanges. The largest estimated increase is of 425% for Relative citations received (coefficient estimate of 0.170, see column 2 in Panel A of Table 8) over the sample mean (0.04, see Table 2). The smallest significant increase is 100% for Relative inventor emigrates (0.010 relative to 0.01, see Table 2).

Under the assumption that PIR adoption in the VCs' home states does not disproportionately increase relative portfolio exchanges through channels other than the portfolio joining event, the results in Panel A of Table 8 suggest that sharing a common VC causally facilitates portfolio exchanges (see Section 5.4 for a relaxation of this identification assumption). Panel B in Table 8 presents the estimates of these causal effects using an instrumental variable (IV) estimation: there is an average increase in relative portfolio exchanges of 329% (relative to the sample means) after joiners enter a VC's portfolio

[26] I aggregate residuals of the different measures of portfolio exchange for every joiner and VC pair using the same methodology to aggregate residuals for $Post_{ijt}$ in Section 4.2. Namely, I regress each measure of portfolio exchange on the VC's home state fixed effects, year dummies, and differential trends across the home states of the VCs. Then, for every joiner and VC pair in the data, the residuals from the years before and after PIR adoption in the VC's home state are aggregated, respectively, into the pre- and post-adoption period observations.

for the first time, which holds for both portfolio exchanges financed by joiners (columns 3, 6, 9) as well as those financed by portfolio companies (columns 2, 5, 8). Across all columns in Panel B, the IV estimates are statistically significant for all relative portfolio exchanges except for Relative inventor immigrants. To produce these IV estimates, I run a two-stage least squares regression of Eq. (2) on the two-period panel of aggregate residuals, where I instrument the variable Post with the PIR dummy. The *F*-test of PIR reported in Panel A (62.76) reveals the instrument's relevance (see Stock and Yogo, 2005).

In Panel C of Table 8, I present the OLS estimates of Eq. (2) on the two-period panel of aggregate residuals as a benchmark against which to compare the IV results of Panel B. Relative to the sample means, the OLS benchmark estimates imply an average increase of 315% in relative portfolio exchanges.

A comparison between the OLS estimates in Panel C of Table 8 and the OLS estimates in Section 4 (reported in Table 3) reveals that the former are substantially larger. The difference in magnitudes between these two groups of OLS estimates is due to differences in sample and methodology between Sections 4 and 5. By construction, the estimates in Table 8 exclude all joiner and VC pairs for which the state of the VC does not adopt PIR (via UPIA enactment) within the estimation period. In addition, the methodology in Table 3 allows for both a mean shift and a trend break after the portfolio joining event. Instead, the methodology behind the estimates in Table 8 does not allow for a trend break, precisely because the purpose of the methodology is to collapse the time series variation into only two time periods per joiner and VC pair. To produce estimates of the results in Section 4 that are more comparable to the ones presented in Table 8, I calculate the implied average increase in portfolio exchanges from results in Section 4 based on a two-period panel data set that also collapses time series variation for every joiner and VC pair into two periods: before and after the joining event (see Online Appendix 3). The implied average increase in relative portfolio exchanges (relative to the mean) based on these estimates is 123%, much higher than the 60% implied average increase of Table 3, and closer to the 315% implied average increase of Table 8. One last discrepancy between the methodologies regards the periods over which the time series variation per joiner and VC pairs is collapsed. In Table 8, this variation is collapsed into pre- and post-PIR adoption periods, whereas in Online Appendix 3, it is collapsed into pre- and post-portfolio-joining-event periods. Since PIR adoption events began only in the 1990s, this discrepancy can explain the higher magnitude of the results in Table 8. Portfolio joining events started as early as 1977, and, on average, the incidence of portfolio exchanges (and cross-company exchanges more generally) is higher after the 1990s than during the 1970s and 1980s.

In addition, a comparison of estimates across Panels B and C in Table 8 reveals that IV estimates are, on average, 4% larger than OLS estimates. This positive difference is not statistically significant, but it makes the interpretation of the results difficult (i.e., one cannot determine how much of the OLS estimate is selection and how much it is treatment), as is common in the venture capital literature (e.g., Kortum and Lerner, 2000; Mollica and Zingales, 2007; Hirukawa and Ueda, 2008; Nanda and Rhodes-Kropf, 2013; Popov and Rosenboom, 2011; see Online Appendix 7).

One potential explanation for the positive difference is that marginal joiners face high costs in attracting VCs absent PIR adoption; for example, Nanda and Rhodes-Kropf (2013) show that VCs usually experiment whenever they have an influx of funds by investing in riskier companies. In that case, IV would yield a "local average treatment effect" above the average marginal effect in the population and potentially above OLS (Angrist and Imbens, 1994). Other potential explanations include measurement error from differences between the enactment and actual implementation dates of PIR (cf., Card, 2001). Against this explanation, the IV estimate also exceeds the OLS estimate when I proxy PIR adoption using UPIA implementation dates (see Online Appendix 8).

5.4. Robustness checks

In this section, I discuss several potential methodological concerns with using PIR adoption as an exogenous determinant of VCs' portfolios and present suggestive evidence against them.

The main methodological concern with the results in Table 8 is that PIR adoption is endogenous to the innovation opportunities of joiners and portfolio companies. That is, PIR adoption anticipates (or leads to venture capital unrelated) changes in innovation opportunities for joiners and portfolio companies. Three additional sets of findings provide evidence against the relative importance of this concern. First, Online Appendix 8 shows no significant evidence of correlated trends between relative portfolio exchanges and PIR adoption, although weak increases are visible three years before adoption for some of the measures. Second, Panel A of Table 9 shows similar results when I restrict the sample to pairs where the joiner and the portfolio companies are not in the home state of the VC.[27] This second set of results point to causal effects as long as PIR adoption in the VC's home state affects relative exchanges between the out-of-state joiners and out-of-state portfolio companies only through the joining event. In support of this assumption, Online Appendix 8 shows no significant evidence of correlated trends in PIR adoption and measures of portfolio exchange in this subsample. The last set of findings mitigating PIR endogeneity concerns show similar results when I further restrict the sample to pairs of joiners and portfolio companies that are also not in coincidental states where PIR is adopted at the same time as in the home state of the VC (see Panel B of Table 9).

A second methodological concern is that the results in Table 8 are driven by aggregate trends that are visible in the plots of average Post against PIR event time (Fig. 4; see discussion in Section 5.1). To address this concern, I restrict the sample to the joiner and VC pairs for which the entire 11-year portfolio joining event time period is within a 20-year interval around the PIR adoption of the VC's home state. Other joiner and VC pairs may have financing events that are too far from the PIR adoption event and are likely to add noise rather than help reduce any potential bias in the OLS estimates. The results are summarized in Online Appendix 8. They show that aggregate trends do not drive the results in Table 8: the reduced form, IV, and OLS estimates are similar for the restricted sample.

A third concern regards the potential driving effect of California or Massachusetts. Against it, Online Appendix 8 shows that results are similar when I drop California and/or Massachusetts from the analysis sample, except for all proxies of inventor exchanges. For these measures, none of the estimates (reduced form, OLS, or IV) are statistically significant. One potential explanation is the enforcement of noncompete agreements imposed in other states during some intervals of the sample period (see Marx,

[27] Only results for inventor-based exchanges do not hold. One interpretation of these results is that the anticipation and facilitation by VCs of "human capital related" portfolio exchanges requires closer monitoring, such as the level of monitoring imposed by VCs that are geographically close to their companies (see Lerner, 1995; Bernstein, Giroud, and Townsend, 2016).

2013). These noncompete agreements restrict the movement of workers across companies and can impede the role of VCs in anticipating and facilitating human capital reallocation inside their portfolios.

A final concern regards potential measurement error in the actual adoption dates of PIR across states, as the average lag between PIR adoption via UPIA enactment and via UPIA implementation is 0.37 years (see Section 5.1). Against this concern, Online Appendix 8 shows that the results are similar if I date PIR adoption using UPIA implementation rather than UPIA enactment (see Online Appendix 5).

6. Conclusion

I show that several proxies of exchanges of innovation resources are prevalent between companies sharing common venture capital investors. Results hold for companies that secure venture capital for plausibly exogenous reasons and in situations where VCs' bargaining power and potential conflicts of interest are low. The data support three novel mechanisms of resource exchange inside portfolios: carve-outs, spawning, and recycling, whereby entrepreneurs divest innovation units, start new ventures, and reuse residual assets in other portfolio companies, respectively. As the successful commercialization of inventions typically requires these cross-company exchanges, the results suggest that returns to innovation are higher inside VC portfolios—although not necessarily appropriated by the original inventors (VCs face a complex set of incentives and hold strong bargaining power over founders). The results help explain why venture capital disproportionately contributes to innovation relative to other financing sources such as corporate investment (Kortum and Lerner, 2000).

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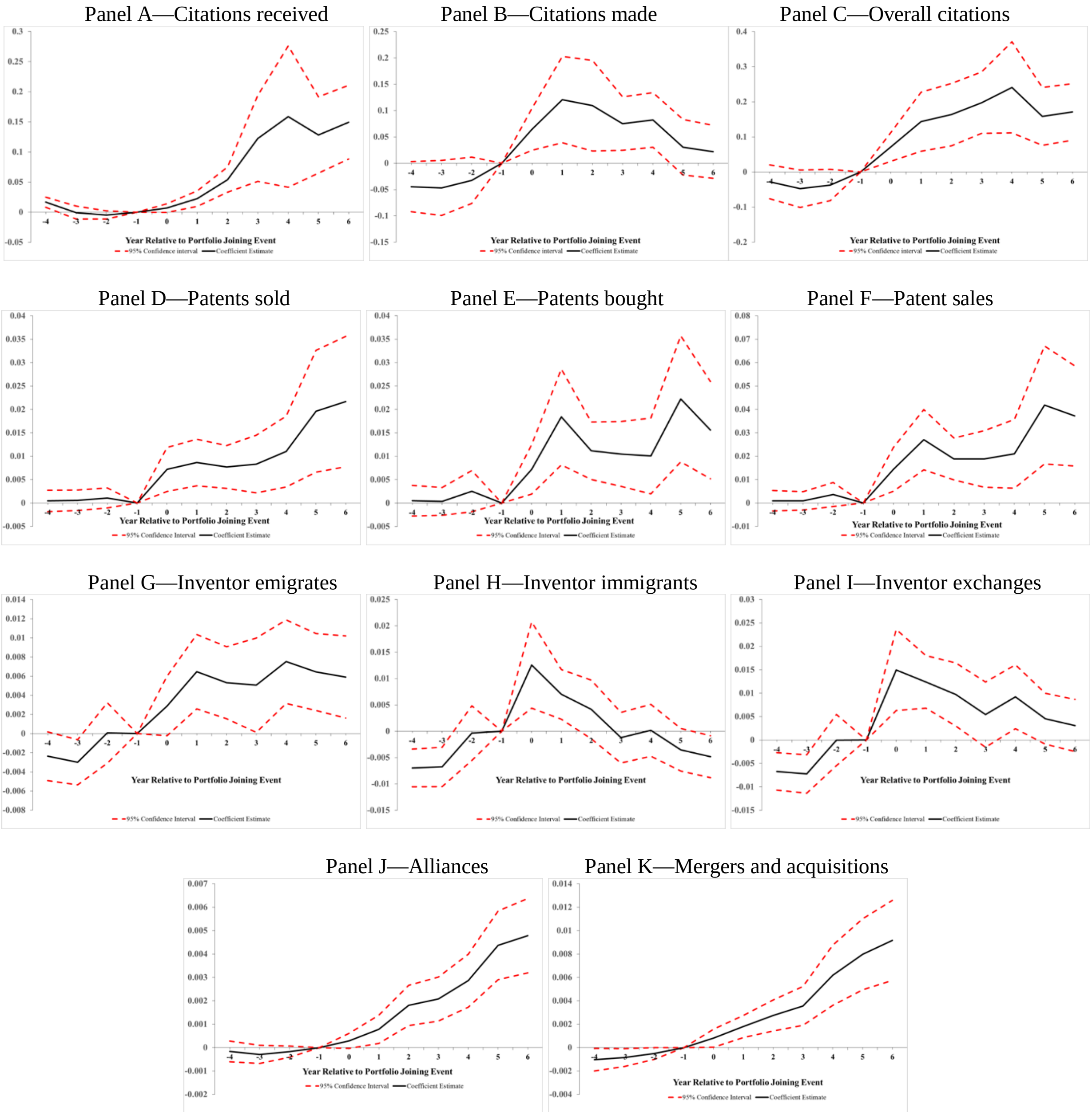
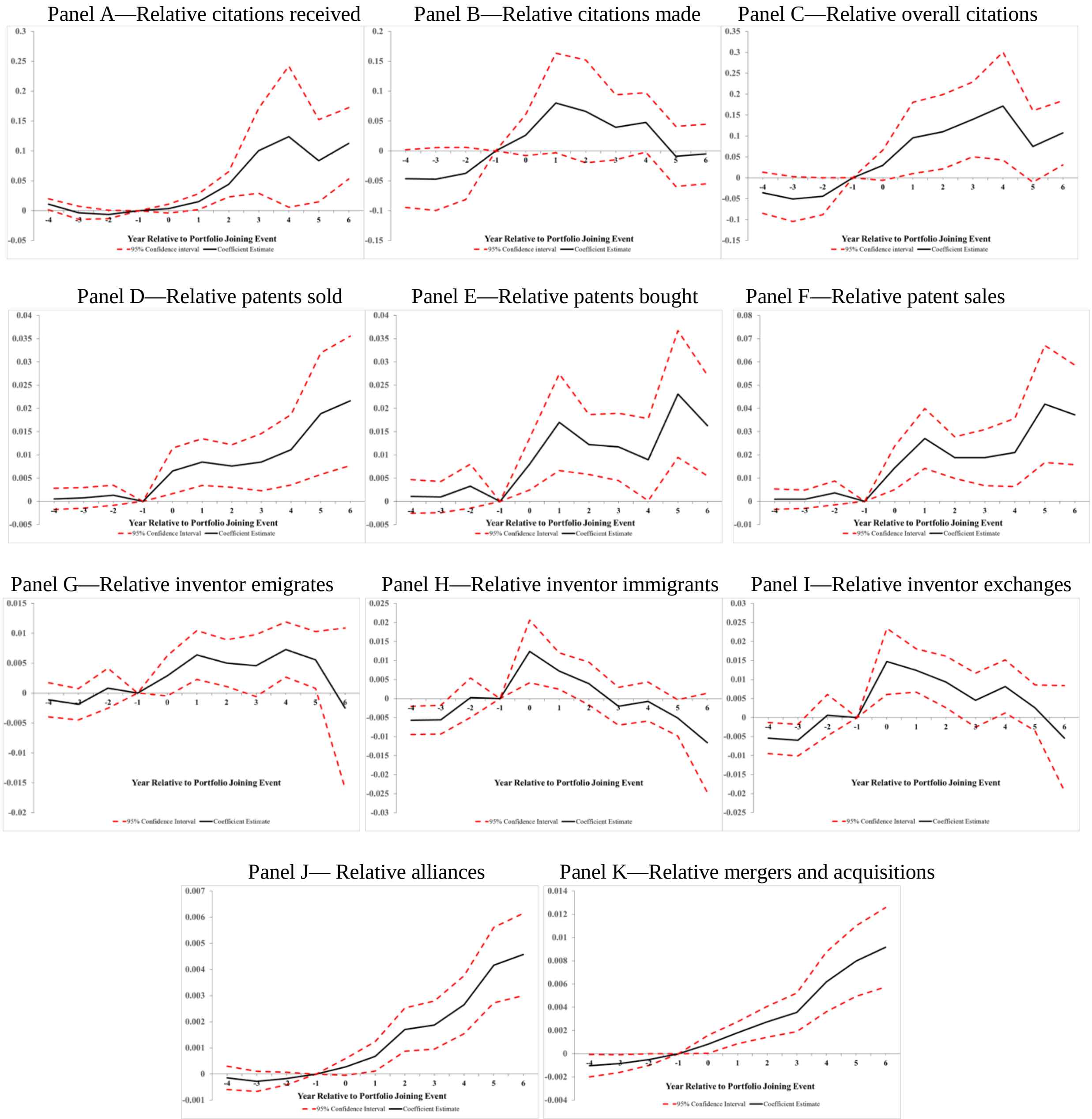
Fig. 1 Patterns in portfolio exchanges around portfolio joining events



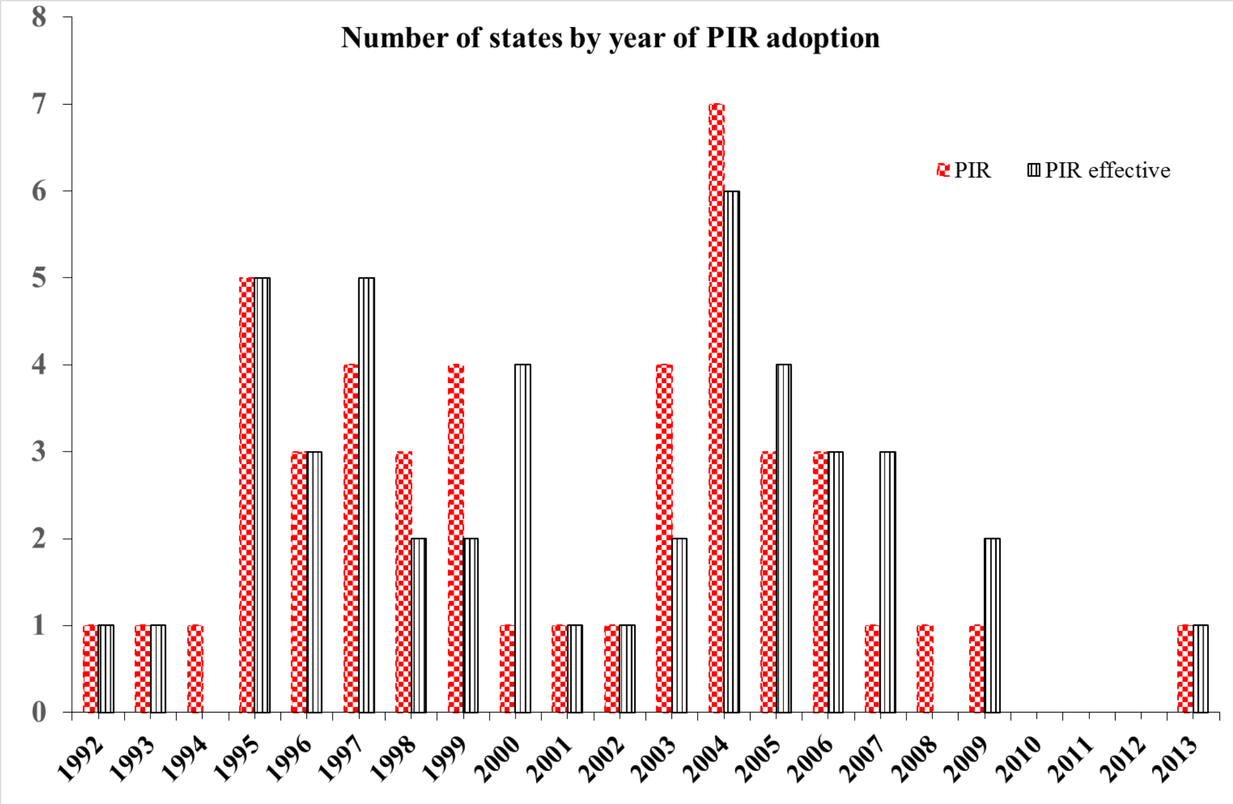
The figure plots the β_τ coefficients on the dummies for years relative to the venture capital portfolio joining event from estimating regression (1) for the different proxies of portfolio exchanges. The event window is five years before and six years after the joiner enters the VC's portfolio for the first time. The dashed lines show the 95% confidence interval on each coefficient; standard errors are clustered at the joiner and VC pair level. Year -1 is the year before the joiner enters the VC's portfolio for the first time. The coefficients are normalized relative to year -1, which is set to zero. All the regressions include joiner and VC pair fixed effects and calendar year fixed effects. An observation is a joiner and VC pair cross time (year).

Fig. 2 Patterns in relative portfolio exchanges around portfolio joining events



The figure plots the β_τ coefficients on the dummies for years relative to the venture capital portfolio joining event from estimating regression (1) for the different proxies of relative portfolio exchanges. The event window is five years before and six years after the joiner enters the VC's portfolio for the first time. The dashed lines show the 95% confidence interval on each coefficient; standard errors are clustered at the joiner and VC pair level. Year -1 is the year before the joiner enters the VC's portfolio for the first time. The coefficients are normalized relative to year -1, which is set to zero. All the regressions include joiner and VC pair fixed effects and calendar year fixed effects. An observation is a joiner and VC pair cross time (year).

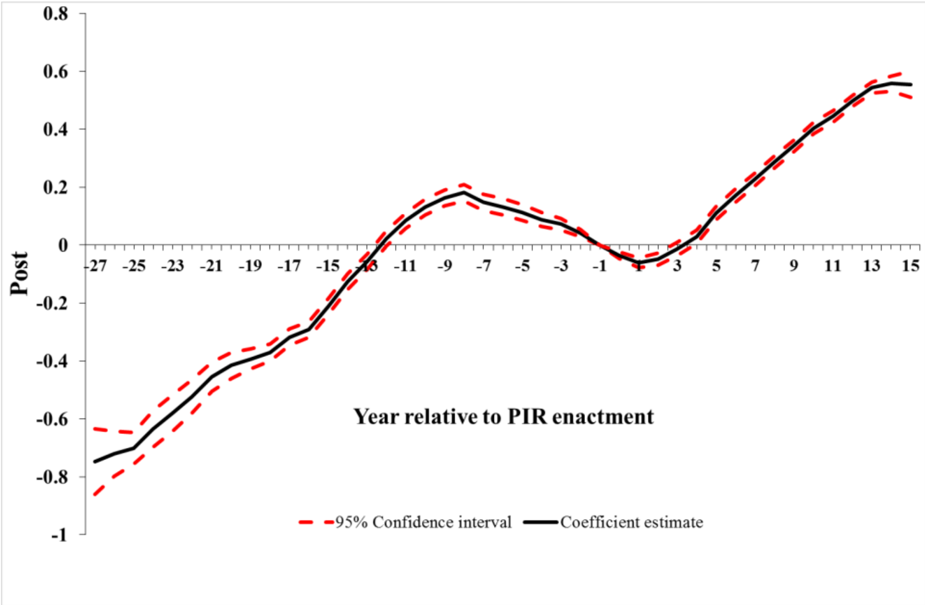
Fig. 3 PIR adoption across US states



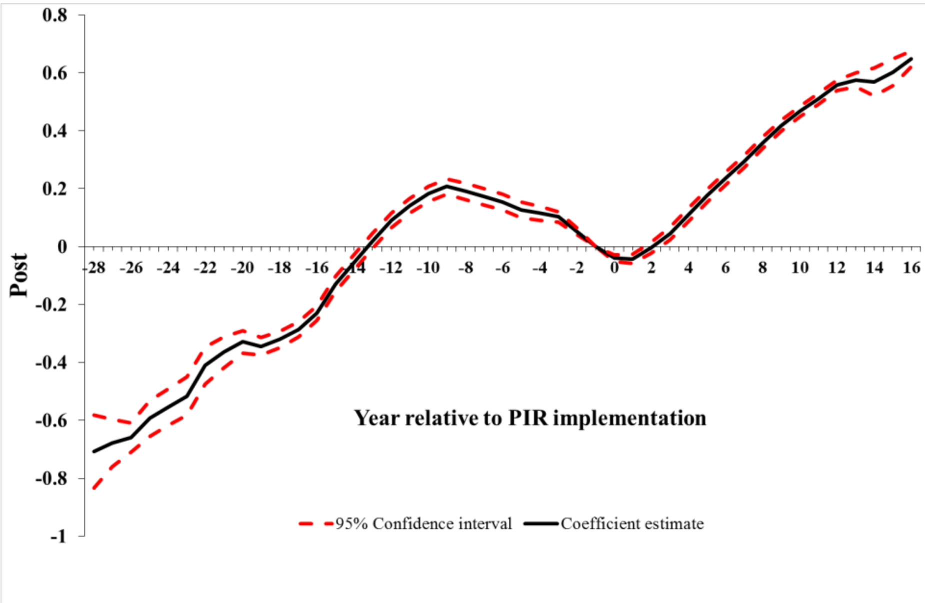
The figure plots the number of US states adopting PIR across time. The red dotted bars indicate years of PIR enactment, as indicated by the corresponding UPIA legislation dates (see Online Appendix 5). The striped black bars indicate the years of the final implementation of PIR, as indicated by the dates in which the corresponding UPIA laws became effective (see Online Appendix 5).

Fig. 4 Probability of joining the VC's portfolio around the year of PIR adoption in VC's home state

Panel A—Probability of joining the VC's portfolio around PIR enactment in VC's home state



Panel B—Probability of joining the VC's portfolio around PIR implementation in VC's home state



The figure plots the coefficients on the dummies for years relative to the time of PIR adoption in the VC's home state (PIR event time dummies), from regressing Post (i.e., a dummy equal to one after the Joiner first enters the VC's portfolio) against the PIR event time dummies. The event window is 29 years before and 16 years after the adoption of PIR in the home state of the VC. The solid (dotted) line plots the estimated coefficients (95th confidence interval) of the PIR event time dummies. The coefficients are normalized relative to the year before PIR adoption, which is set to zero. All the regressions include VC's home state fixed effects. An observation is a joiner and VC pair cross year. Panel A uses information on PIR adoption via enactment (i.e., when the law was approved by the local government), and Panel B on PIR adoption via implementation (i.e., when the law became effective); see Online Appendix 5 and Fig. 3. Joiner and VC pairs where the VC is located in a state with no PIR adoption in the sample are excluded from the plots by design.

Table 1

Sample composition

Panel A. Distribution over time of venture capital portfolio joining events and patent awards

	Venture capital portfolio joining events					Patent awards	
	Total	Seed	Early stage	Expansion	Later stage	Patent filings	Patent grants
1976						10	7
1977	6	5	1	0	0	26	10
1978	12	10	0	2	0	28	19
1979	23	9	7	7	0	44	27
1980	86	55	15	15	1	51	40
1981	219	121	49	42	7	124	33
1982	260	103	66	69	22	166	89
1983	348	156	77	87	28	197	154
1984	336	159	79	81	17	268	184
1985	341	134	62	115	30	340	239
1986	290	132	58	66	34	442	380
1987	275	134	67	57	17	558	427
1988	270	114	77	66	13	718	660
1989	343	115	94	102	32	834	679
1990	221	78	43	83	17	1,026	802
1991	165	39	49	61	16	1,170	1,002
1992	184	54	39	72	19	1,407	1,161
1993	200	78	58	46	18	1,730	1,356
1994	216	77	60	44	35	2,357	1,560
1995	278	97	97	64	20	3,816	2,006
1996	244	71	61	91	21	4,066	2,493
1997	343	75	123	99	46	5,066	3,985
1998	571	140	205	169	57	5,252	4,309
1999	810	122	269	321	98	5,867	4,710
2000	1,171	71	480	473	147	6,918	5,088
2001	856	73	330	362	91	7,640	5,385
2002	721	46	247	304	124	7,558	6,013
2003	807	52	260	299	196	5,889	5,888
2004	743	43	192	278	230	5,118	5,464
2005	559	23	144	203	189	3,708	7,159
2006	395	22	102	146	125	1,836	6,769
2007	335	24	63	124	124	516	6,673
2008	187	12	39	71	65	25	7
Total	11,815	2,390	1,278	288	1,747	74,771	74,771

Panel B. Distribution of patents and joiners across states (Top 10 states)

	Patents	% Patents	Joiners	% Joiners	Venture capital firms	% Venture capital firms
CA	39,393	56.04	1,845	46.59	415	32.81
MA	6,913	9.83	517	13.06	139	10.99
TX	5,056	7.19	191	4.82	60	4.74
CO	2,589	3.68	110	2.78	32	2.53
WA	2,098	2.98	121	3.06	33	2.61
PA	1,115	1.59	111	2.8	35	2.77
NJ	1,022	1.45	106	2.68	24	1.9
NY	993	1.41	100	2.53	130	10.28
IL	966	1.37	71	1.79	46	3.64
MN	864	1.23	63	1.59	28	2.21

Panel C. Distribution of patents across 2-digit technology classes (Top 10 classes)

Technology class	Name	Number	% Patents
22	Computer Hardware and Software	13,000	17.39
21	Communications	8,142	10.89
46	Semiconductor Devices	7,159	9.57

32	Surgery & Medical Instruments	6,589	8.81
24	Information Storage	5,818	7.78
31	Drugs	4,736	6.33
33	Biotechnology	3,753	5.02
41	Electrical Devices	3,302	4.42
19	Miscellaneous Chemical	2,724	3.64
45	Power Systems	2,266	3.03

Panel D. Industry distribution of joiners

Industries	Number of joiners	% of joiners
Medical health	699	17.65
Semiconductors	659	16.64
Computer software	649	16.39
Communications and media	446	11.26
Biotechnology	432	10.91
Internet specific	363	9.17
Computer hardware	342	8.64
Industrial energy	250	6.31
Other products	67	1.69
Consumer related	53	1.34
Total	3,960	100

The final sample includes information for 3,960 joiners that filed 74,771 patents (approximately 2.5% of all patent awards) and first entered the portfolio of one of 1,265 VCs during 1976-2008. The data include 11,815 portfolio joining events. All additional financing rounds by an existing VC investor are not counted as portfolio joining events. In Panel B, the joiner's home state is retrieved from the SDC data set. For some joiners, this information is missing. I used web searches based on the joiner's name to fill in the missing information. For 649 joiners, the web search returned no information, most likely because they are no longer active. In very few cases, the joiner's home state differs from the location of the inventor reported in the patent filings (<5%). In Panel C, I reclassified the three-digit technology classes of patents into two-digit classes using the method by Hall, Jaffe, and Trajtenberg (2001). In Panel D, I retrieve industry classification from the SDC data set.

Table 2

Summary statistics

	Observations	Mean	Std. Dev.	Min	Max
Citations received	121,553	0.05	1.50	0.00	263.00
Citations made	121,553	0.10	2.35	0.00	249.00
Overall citations	121,553	0.15	2.81	0.00	263.00
Patents sold	121,553	0.01	0.23	0.00	41.00
Patents bought	121,553	0.01	0.24	0.00	22.00
Patent sales	121,553	0.02	0.39	0.00	41.00
Inventor emigrates	121,553	0.01	0.12	0.00	8.00
Inventor immigrants	121,553	0.01	0.17	0.00	12.00
Inventor exchanges	121,553	0.02	0.21	0.00	12.00
Alliances	121,553	0.001	0.034	0.00	1.00
Mergers and acquisitions	121,553	0.002	0.043	0.00	1.00
Matched citations received	121,553	0.01	0.56	0.00	120.00
Matched citations made	121,553	0.03	0.74	0.00	119.00
Matched overall citations	121,553	0.04	0.97	0.00	132.00
Matched patents sold	121,553	0.00	0.02	0.00	4.00
Matched patents bought	121,553	0.00	0.08	0.00	20.00
Matched patent sales	121,553	0.00	0.08	0.00	20.00
Matched inventor emigrates	121,553	0.00	0.11	0.00	30.00
Matched inventor immigrants	121,553	0.00	0.11	0.00	30.00
Matched inventor exchanges	121,553	0.00	0.11	0.00	30.00
Matched alliances	121,553	0.000	0.008	0.00	1.00
Matched mergers and acquisitions	121,553	0.000	0.000	0.00	0.00
Relative citations received	121,553	0.04	1.59	-120.00	263.00
Relative citations made	121,553	0.07	2.39	-104.00	249.00
Relative overall citations	121,553	0.11	2.91	-131.00	262.00
Relative patents sold	121,553	0.01	0.23	-4.00	41.00
Relative patents bought	121,553	0.01	0.25	-20.00	22.00
Relative patent sales	121,553	0.02	0.40	-20.00	41.00
Relative inventor emigrates	121,553	0.01	0.16	-30.00	8.00
Relative inventor immigrants	121,553	0.01	0.20	-30.00	12.00
Relative inventor exchanges	121,553	0.01	0.23	-30.00	12.00
Relative alliances	121,553	0.001	0.035	-1.00	1.00
Relative mergers and acquisitions	121,553	0.002	0.043	0.00	1.00
Post	121,553	0.61	0.49	0.00	1.00
Year	121,553	1997	7.85	1976	2008
Year financing	121,553	1996	7.54	1977	2008
Young company	120,610	0.59	0.49	0.00	1.00
Early stage	121,553	0.43	0.49	0.00	1.00
Junior VC	111,383	0.51	0.50	0.00	1.00
Specialist VC	116,452	0.10	0.29	0.00	1.00

This table presents the summary statistics of the main variables used in the empirical analysis. Observations are at the joiner and VC pair cross time (year). Section 3 has a detailed explanation of the variables.

Table 3

Portfolio exchanges between joiners and portfolio companies

Panel A—Portfolio exchanges

Dependent variable	(1) Citations received	(2) Citations made	(3) Overall citations	(4) Patents sold	(5) Patents bought	(6) Patent sales	(7) Inventor emigrates	(8) Inventor immigrants	(9) Inventor exchanges	(10) Alliances	(11) Mergers and acquisitions
Post	0.021***	0.100***	0.121***	0.005***	0.009***	0.014***	0.003**	0.007***	0.011***	0.000	0.000
	(0.006)	(0.022)	(0.023)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)
Post× Event-Trend	0.033***	-0.026**	0.007	0.002***	0.001	0.003***	-0.001	-0.006***	-0.005***	0.001***	0.001***
	(0.005)	(0.011)	(0.012)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.211	0.312	0.293	0.183	0.196	0.222	0.587	0.633	0.605	0.476	0.422

Panel B—Relative portfolio exchanges

Dependent variable	(1) Relative Citations Received	(2) Relative Citations Made	(3) Relative Overall Citations	(4) Relative Patents Sold	(5) Relative Patents Bought	(6) Relative Patent Sales	(7) Relative Inventor Emigrates	(8) Relative Inventor Immigrants	(9) Relative Inventor Exchanges	(10) Relative Alliances	(11) Relative Mergers and Acquisitions
Post	0.018***	0.060***	0.078***	0.004***	0.009***	0.014***	0.005***	0.008***	0.012***	0.000	0.000
	(0.007)	(0.022)	(0.023)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)
Post×Event-Trend	0.024***	-0.025**	-0.001	0.002***	0.001	0.004***	-0.001*	-0.006***	-0.005***	0.001***	0.001***
	(0.005)	(0.011)	(0.012)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.196	0.291	0.267	0.182	0.187	0.217	0.517	0.591	0.571	0.471	0.422

This table reports the coefficients and standard errors (in parentheses) from estimating Eq. (2) on the different proxies of portfolio exchanges. An observation is a joiner and VC pair cross time (year). The explanatory variables of interest are Post, an indicator variable that equals one after the joiner enters the VC portfolio for the first time, and Post×Event-Trend, which equals zero before the joiner enters the VC portfolio for the first time and indicates the first through sixth years after the joiner enters the portfolio. Standard errors are heteroskedasticity robust and clustered at the joiner and VC pair level.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4

Heterogeneity I: Relative portfolio exchanges between joiners and portfolio companies

Dependent variable	(1) Relative citations received	(2) Relative citations made	(3) Relative overall citations	(4) Relative patents sold	(5) Relative patents bought	(6) Relative patent sales	(7) Relative Inventor Emigrates	(8) Relative inventor immigrants	(9) Relative inventor exchanges	(10) Relative alliances	(11) Relative mergers and acquisitions
Panel A—Age joiner											
Young											
Post	0.019**	0.116***	0.135***	0.002	0.008**	0.010**	0.005**	0.013***	0.017***	0.000	-0.001***
	(0.008)	(0.035)	(0.037)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.000)	(0.000)
Post× Event-Trend	0.028***	-0.033*	-0.005	0.002***	0.001	0.003**	-0.000	-0.008***	-0.006***	0.001***	0.002***
	(0.006)	(0.018)	(0.019)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	71,181	71,181	71,181	71,181	71,181	71,181	71,181	71,181	71,181	71,181	71,181
R-2	0.206	0.293	0.282	0.180	0.164	0.192	0.181	0.164	0.187	0.465	0.349
Old											
Post	0.016	-0.025	-0.009	0.009***	0.012***	0.021***	0.005**	0.002	0.006	-0.000	0.001**
	(0.012)	(0.018)	(0.021)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.000)	(0.001)
Post× Event-Trend	0.020**	-0.013	0.007	0.004**	0.003	0.007**	-0.002**	-0.003**	-0.003**	0.001***	0.001**
	(0.009)	(0.012)	(0.016)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	49,429	49,429	49,429	49,429	49,429	49,429	49,429	49,429	49,429	49,429	49,429
R-2	0.185	0.280	0.228	0.182	0.207	0.233	0.135	0.161	0.165	0.481	0.478
p-value F-tests											
Post	0.84	0.00	0.00	0.04	0.44	0.12	0.79	0.02	0.04	0.67	0.00
Post× Event-Trend	0.45	0.33	0.62	0.32	0.25	0.23	0.12	0.01	0.08	0.95	0.12
Panel B—Stage joiner											
Early											
Post	0.003	0.061**	0.063**	0.005*	0.009**	0.014***	0.006***	0.017***	0.021***	-0.000	-0.001**
	(0.005)	(0.028)	(0.029)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)	(0.004)	(0.000)	(0.000)
Post× Event-Trend	0.018***	-0.001	0.017*	0.002	0.001	0.003	-0.000	-0.008***	-0.006***	0.001***	0.002***
	(0.005)	(0.009)	(0.010)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	51,803	51,803	51,803	51,803	51,803	51,803	51,803	51,803	51,803	51,803	51,803
R-2	0.181	0.286	0.274	0.241	0.209	0.251	0.167	0.158	0.179	0.361	0.329
Late											
Post	0.027***	0.060*	0.088**	0.004*	0.009***	0.013***	0.004*	0.002	0.005	0.000	0.001
	(0.011)	(0.033)	(0.035)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.000)	(0.000)
Post× Event-Trend	0.027***	-0.041**	-0.014	0.003***	0.001	0.004**	-0.002**	-0.005***	-0.004***	0.001***	0.001**
	(0.008)	(0.018)	(0.020)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	69,750	69,750	69,750	69,750	69,750	69,750	69,750	69,750	69,750	69,750	69,750
R-2	0.198	0.293	0.266	0.150	0.170	0.187	0.149	0.167	0.177	0.524	0.471

p-value F-tests											
Post	0.03	0.99	0.59	0.70	0.96	0.88	0.56	0.00	0.00	0.21	0.01
Post× Event-Trend	0.36	0.04	0.16	0.36	0.89	0.66	0.09	0.05	0.22	0.40	0.01
Panel C—Joiner is new to venture capital											
New to Venture Capital											
Post	0.020**	0.086**	0.106***	0.004	0.008**	0.012***	0.005**	0.012***	0.015***	0.000	-0.001**
	(0.009)	(0.034)	(0.036)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.000)	(0.000)
Post× Event-Trend	0.025***	-0.022*	0.003	0.003***	0.002	0.005***	0.000	-0.006***	-0.005***	0.001***	0.001***
	(0.006)	(0.012)	(0.013)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	71,077	71,077	71,077	71,077	71,077	71,077	71,077	71,077	71,077	71,077	71,077
R-2	0.211	0.278	0.270	0.183	0.189	0.223	0.168	0.168	0.184	0.428	0.367
Already Secured Venture Capital											
Post	0.018	0.024	0.042	0.005***	0.011***	0.016***	0.005*	0.004	0.008**	-0.000	0.001
	(0.012)	(0.025)	(0.027)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.000)	(0.001)
Post× Event-Trend	0.024**	-0.030	-0.007	0.001	0.001	0.002	-0.003**	-0.006***	-0.005***	0.001***	0.001**
	(0.010)	(0.021)	(0.023)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)
Obs.	50,476	50,476	50,476	50,476	50,476	50,476	50,476	50,476	50,476	50,476	50,476
R-2	0.181	0.317	0.263	0.182	0.185	0.201	0.146	0.160	0.170	0.509	0.466
p-value F-tests											
Post	0.88	0.14	0.15	0.60	0.58	0.50	0.98	0.08	0.15	0.74	0.03
Post× Event-Trend	0.92	0.73	0.72	0.15	0.51	0.21	0.03	0.71	0.96	0.91	0.09
Panel D—VC experience											
Junior											
Post	0.011	-0.001	0.010	0.006***	0.010***	0.016***	0.003	0.002	0.005	0.000	-0.000
	(0.007)	(0.007)	(0.010)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.000)	(0.000)
Post× Event-Trend	0.013***	-0.000	0.013**	0.003*	0.003*	0.005**	0.000	-0.002*	-0.000	0.001***	0.001*
	(0.005)	(0.002)	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	57,344	57,344	57,344	57,344	57,344	57,344	57,344	57,344	57,344	57,344	57,344
R-2	0.224	0.277	0.254	0.234	0.288	0.294	0.143	0.142	0.167	0.476	0.387
Senior											
Post	0.028**	0.140***	0.168***	0.003	0.010**	0.013**	0.009***	0.019***	0.025***	-0.000	-0.000
	(0.014)	(0.051)	(0.053)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.005)	(0.000)	(0.001)
Post× Event-Trend	0.033***	-0.059***	-0.026	0.003**	0.000	0.003	-0.002**	-0.011***	-0.011***	0.001***	0.002***
	(0.009)	(0.022)	(0.024)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)
Obs.	54,028	54,028	54,028	54,028	54,028	54,028	54,028	54,028	54,028	54,028	54,028
R-2	0.193	0.292	0.269	0.182	0.166	0.202	0.182	0.180	0.191	0.488	0.446
p-value F-tests											
Post	0.26	0.01	0.00	0.37	0.93	0.63	0.07	0.00	0.00	0.51	0.94
Post× Event-Trend	0.06	0.01	0.11	0.93	0.23	0.49	0.09	0.00	0.00	0.48	0.04

This table reports the coefficients and standard errors (in parentheses) from estimating Eq. (2) on the different proxies of relative portfolio exchanges. An observation is a joiner and VC pair cross time (year). The explanatory variables of interest are Post, an indicator variable that equals one after the joiner enters the VC portfolio for the first time, and Post×Event-Trend, which equals zero before the joiner enters the VC portfolio for the first time, and indicates the first through sixth years after the joiner enters the portfolio. In Panel A, the age of the joiner is estimated as the difference between the year the company joins the portfolio of the VC and the founding year, as reported in SDC. Young (Old) are joiners below (above) the median joiner age in the sample of two years. In Panel B, joiners are defined as early if the first investment they secured from a VC was either at a seed or early stage round according to the SDC files, following Lindsey (2008). In Panel C, I define a joiner as new to venture capital if the joiner is securing venture capital for the first time. In Panel D, investor experience is measured by the number of prior investments made by the VC following Lindsey (2008). Junior (Senior) are VCs that are below (above) the median VC experience in the sample of six years. Standard errors are heteroskedasticity robust and clustered at the joiner and VC pair level.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Heterogeneity II: relative portfolio exchanges between joiners and portfolio companies

Dependent variable	(1) Relative citations received	(2) Relative citations made	(3) Relative overall citations	(4) Relative patents sold	(5) Relative patents bought	(6) Relative patent sales	(7) Relative inventor emigrates	(8) Relative inventor immigrants	(9) Relative inventor exchanges	(10) Relative alliances	(11) Relative mergers and acquisitions
					Panel A—Industry of joiner and portfolio companies						
Same industry											
Post	0.014*	0.112***	0.126***	0.005**	0.007**	0.012***	0.004**	0.006**	0.009***	0.000	-0.000
	(0.008)	(0.040)	(0.041)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)
Post× Event-Trend	0.015**	-0.006	0.010	0.002**	0.002	0.004*	-0.000	-0.004***	-0.003***	0.000***	0.001***
	(0.007)	(0.007)	(0.010)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.193	0.245	0.233	0.230	0.192	0.235	0.142	0.152	0.166	0.444	0.445
Different industry											
Post	-0.000	-0.091***	-0.092***	-0.001	0.002***	0.001	0.002	0.004**	0.005**	-0.000	0.000
	(0.003)	(0.025)	(0.025)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
Post× Event-Trend	-0.001	-0.017**	-0.018**	0.000	-0.000	0.000	-0.001*	-0.002***	-0.003***	0.000**	0.001***
	(0.003)	(0.008)	(0.009)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.132	0.177	0.173	0.097	0.120	0.113	0.155	0.165	0.172	0.488	0.387
					Panel B—VC fund of joiner and portfolio companies						
Same fund											
Post	0.008	0.007	0.015	0.005**	0.009***	0.014***	0.002	0.001	0.003	0.000	0.000
	(0.007)	(0.025)	(0.026)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)
Post× Event-Trend	0.002	-0.001	0.001	0.002*	0.002	0.004*	-0.001*	-0.001	-0.002*	0.000***	0.000*
	(0.005)	(0.005)	(0.007)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.187	0.222	0.206	0.185	0.202	0.220	0.130	0.137	0.137	0.418	0.457
Different fund											
Post	0.007	0.013	0.020	-0.001	-0.000	-0.001	0.004**	0.009***	0.011***	-0.001	-0.000
	(0.005)	(0.027)	(0.028)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.000)
Post× Event-Trend	0.013**	-0.022**	-0.010	0.001	-0.000	0.001	-0.000	-0.005***	-0.004***	0.001	0.001***
	(0.005)	(0.011)	(0.012)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.177	0.266	0.246	0.148	0.136	0.170	0.156	0.174	0.183	0.148	0.407

This table reports the coefficients and standard errors (in parentheses) from estimating Eq. (2) on the different proxies of relative portfolio exchanges. An observation is a joiner and VC pair cross time (year). The explanatory variables of interest are Post, an indicator variable that equals one after the joiner enters the VC portfolio for the first time, and Post×Event-Trend, which equals zero before the joiner enters the VC portfolio for the first time, and indicates the first through sixth years after the joiner enters the portfolio. In Panel A, I consider the six broad industry sectors defined by SDC: biotechnology, communications and media, computer-related, medical, non high technology, and semiconductors (see Table 1). Standard errors are heteroskedasticity robust and clustered at the joiner and VC pair level.*,

, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Inventor and executive exchanges into (and from) incumbent and future portfolio companies

Panel A—Inventor exchanges

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Relative inventor emigrates	Relative Inventor immigrants	Relative inventor exchanges	Relative Inventor emigrates incumbent	Relative inventor immigrants incumbent	Relative inventor exchanges incumbent	Relative inventor emigrates future	Relative Inventor Immigrants future	Relative inventor exchanges future
Post	0.005***	0.008***	0.012***	0.001	0.007***	0.008***	0.003***	0.001	0.004***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Post× Event-Trend	-0.001*	-0.006***	-0.005***	-0.001***	-0.005***	-0.005***	0.000	-0.001**	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.517	0.591	0.571	0.147	0.172	0.173	0.159	0.159	0.171
Mean dep. var.	0.005	0.009	0.014	0.002	0.008	0.009	0.004	0.002	0.005

Panel B—Executive Exchanges

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Executives emigrates	Executives immigrants	Executive exchanges	Executives emigrates incumbent	Executives immigrants incumbent	Executives exchanges incumbent	Executives emigrates future	Executives immigrants future	Executives exchanges future
Post	0.008***	0.014***	0.020***	0.000	0.014***	0.012***	0.008***	0.001	0.008***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Post× Event-Trend	-0.002***	-0.009***	-0.010***	-0.002***	-0.008***	-0.009***	-0.000*	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.160	0.112	0.147	0.115	0.112	0.117	0.149	0.102	0.146
Mean dep. var.	0.006	0.008	0.013	0.002	0.007	0.008	0.004	0.001	0.005

Panel C—Coincidence inventor and executive exchanges

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Inventor emigrates	Inventor immigrants	Inventor exchanges	Conditional inventor emigrates	Conditional inventor immigrants	Conditional inventor exchanges
Post	0.003**	0.007***	0.010***	0.000	0.001***	0.001***
	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)
Post× Event-Trend	-0.001	-0.005***	-0.005***	-0.000	-0.000***	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obs.	120,955	120,955	120,955	121,553	121,553	121,553
R-2	0.161	0.177	0.189	0.127	0.099	0.124
Sample	Executives do not leave	Executives do not leave	Executives do not leave	All	All	All
Mean dep. var.	0.006	0.010	0.015	0.0003	0.0003	0.0006

This table reports the coefficients and standard errors (in parentheses) from estimating Eq. (2) on the different proxies of portfolio exchanges. An observation is a joiner and VC pair cross time (year). The explanatory variables of interest are Post, an indicator variable that equals one after the joiner enters the VC portfolio for the first time, and Post×Event-Trend, which equals zero before the joiner enters the VC portfolio for the first time, and indicates the first through sixth years after the joiner enters the portfolio. The dependent variable is specified at the top of each column. The sample used in the first three columns of Panel C restricts observations to those where no executives leave the joiner to work in another portfolio company. Standard errors are heteroskedasticity robust and clustered at the joiner and VC pair level.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Grouped and individual inventor exchanges

Panel A—Inventor exchanges

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	At least one inventor emigrates	At least one inventor immigrates	Individual inventor emigrates	Individual inventor immigrates	Team of inventors emigrates	Team of inventors immigrates
Post	0.001*	0.003***	0.001	0.002*	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Post× Event-Trend	-0.000	-0.003***	-0.000	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	121,553	121,553	121,553	121,553	121,553	121,553
R-2	0.155	0.163	0.126	0.121	0.147	0.170

Panel B —Circumstances surrounding emigration of teams of inventors

Merger and acquisition outside the portfolio	21	22%
Merger and acquisition incumbent portfolio company	7	7%
Merger and acquisition future portfolio company	3	3%
Liquidation	3	3%
Foundation	34	36%
IPO	2	2%
Reorganization	7	7%
Unclassifiable	18	19%

Panel A reports the coefficients and standard errors (in parentheses) from estimating Eq. (2) on the different proxies of portfolio exchanges. An observation is a joiner and VC pair cross time (year). The explanatory variables of interest are Post, an indicator variable that equals one after the joiner enters the VC portfolio for the first time, and Post×Event-Trend, which equals zero before the joiner enters the VC portfolio for the first time, and indicates the first through sixth years after the joiner enters the portfolio. The dependent variable is specified at the top of each column. Standard errors are heteroskedasticity robust and clustered at the joiner and VC pair level.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Panel B classifies the circumstances surrounding emigration of teams of inventors from joiners to portfolio companies. There are a total of 73 Joiners for which at least one team of inventors emigrates to another portfolio company. There are a total of 95 emigration events of teams of inventors. I classify the circumstances surrounding such migrations into seven categories of corporate events (merger or acquisition by a company outside the VC portfolio, merger or acquisition by an incumbent portfolio company, merger or acquisition by a future portfolio company, IPO, liquidation, restructuring and founding) by comparing the timing of the emigration and the timing of such corporate events. An emigration event is classified as a respective corporate event if it occurs within four years of the corporate event. The class "reorganization" includes several types of corporate events including: hiring of new CEOs, securing investment from government, and opening a foreign subsidiary. An emigration event is unclassifiable if it does not take place within four years of the six corporate events considered.

Table 8

PIR Adoption and relative portfolio exchanges between joiners and portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable (Residuals of):	Post	Relative citations received	Relative citations made	Relative overall citations	Relative patents sold	Relative patents Bought	Relative patent sales	Relative inventor emigrates	Relative inventor immigrants	Relative inventor exchanges	Relative alliances	Relative mergers and acquisitions
							Panel A —Reduced Form					
PIR	0.618***	0.170***	0.120***	0.290***	0.012***	0.015***	0.027***	0.010**	0.004	0.014**	0.004***	0.006***
	(0.078)	(0.052)	(0.040)	(0.090)	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)	(0.006)	(0.001)	(0.001)
Observations	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694
R-squared	0.888	0.516	0.724	0.632	0.639	0.547	0.599	0.589	0.619	0.605	0.736	0.690
F- exc. instruments	62.76											
							Panel B — IV					
Post		0.276***	0.193***	0.469***	0.019***	0.024***	0.043***	0.015***	0.006	0.022***	0.007***	0.009***
		(0.054)	(0.044)	(0.094)	(0.003)	(0.006)	(0.009)	(0.005)	(0.004)	(0.008)	(0.001)	(0.002)
Observations		7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694
R-squared		0.516	0.724	0.633	0.639	0.547	0.599	0.590	0.619	0.606	0.736	0.689
							Panel C —OLS					
Post		0.273***	0.196***	0.469***	0.018***	0.019***	0.037***	0.016***	0.007*	0.024***	0.007***	0.007***
		(0.062)	(0.054)	(0.114)	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.001)	(0.001)
Observations		7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694
R-squared		0.516	0.724	0.633	0.639	0.547	0.599	0.590	0.619	0.606	0.736	0.689

Panel A in this table reports the coefficients and standard errors (in parentheses) from estimating Eq. (3). An observation is a joiner and VC pair cross time, where time has been collapsed into two periods: pre- and post-PIR adoption in the VC's home state. The dependent variables correspond to the aggregate residuals from regressions of the outcome variables on year fixed effects, differential trends across the home states of VCs, and fixed effects at the level of the home state of the VC, which are then collapsed to two observations per joiner and VC pair: before and after the home state of the VC adopts PIR. PIR is an indicator that equals one after the home state of the VC adopts PIR via UPIA enactment (see Online Appendix 3). Panel B of this table reports IV estimates of Eq. (2) in the two-period panel (i.e., pre and post for every pair), where I instrument Post using PIR. Panel C of this table reports OLS estimates of Eq. (2) on the two-period panel. The event window includes all observations from joiner and VC pairs for which the VC's home state adopted PIR within the sample period and corresponds to 29 years before and 16 years after the adoption of PIR in the home state of the VC. Standard errors are heteroskedasticity robust and clustered at the home state of the VC level throughout.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9

Robustness checks: PIR adoption and relative portfolio exchanges between joiners and portfolio companies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)/	(10)	(11)	(12)
Dependent variable (residuals of):	Post	Relative citations received	Relative citations made	Relative overall citations	Relative patents sold	Relative patents bought	Relative patent sales	Relative inventor emigrates	Relative inventor immigrants	Relative inventor exchanges	Relative alliances	Relative mergers and acquisitions
Panel A—Joiners and portfolio companies out of the home state of the VC												
Reduced form												
PIR	0.578***	0.077**	0.055**	0.132***	0.011***	0.013***	0.024***	0.001	0.001	-0.002	0.002*	0.004***
	(0.056)	(0.034)	(0.025)	(0.047)	(0.002)	(0.004)	(0.006)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870
R-squared	0.878	0.521	0.664	0.611	0.720	0.556	0.622	0.631	0.527	0.641	0.652	0.791
F- exc. instruments	106.53											
OLS												
Post		0.089	0.073	0.162*	0.018***	0.017***	0.035***	0.004	0.003	-0.002	0.003**	0.004***
		(0.055)	(0.044)	(0.083)	(0.004)	(0.004)	(0.007)	(0.005)	(0.003)	(0.004)	(0.001)	(0.001)
Observations		3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870
R-squared		0.520	0.663	0.610	0.720	0.555	0.622	0.631	0.527	0.641	0.652	0.790
IV												
Post		0.133*	0.096*	0.228**	0.018***	0.023***	0.041***	0.001	0.001	-0.004	0.003**	0.007***
		(0.067)	(0.048)	(0.098)	(0.003)	(0.007)	(0.010)	(0.006)	(0.004)	(0.004)	(0.002)	(0.002)
Observations		3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870	3,870
R-squared		0.520	0.663	0.610	0.720	0.555	0.622	0.631	0.527	0.641	0.652	0.790
Panel B— Joiners and portfolio companies out of the home state of the VC and out of coincidental states												
Reduced form												
PIR	0.568***	0.068**	0.052**	0.120***	0.012***	0.011***	0.023***	0.000	0.000	-0.003	0.001	0.004***
	(0.054)	(0.025)	(0.024)	(0.040)	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618
R-squared	0.879	0.681	0.524	0.625	0.566	0.722	0.632	0.634	0.528	0.645	0.654	0.801
F- exc. instruments	110.64											
OLS												
Post		0.097**	0.070*	0.167**	0.015***	0.018***	0.034***	0.003	0.002	-0.003	0.002	0.004***
		(0.043)	(0.037)	(0.070)	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)	(0.004)	(0.002)	(0.001)
Observations		3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618
R-squared		0.681	0.524	0.624	0.565	0.722	0.632	0.635	0.528	0.645	0.654	0.800
IV												
Post		0.120**	0.092*	0.212**	0.022***	0.019***	0.041***	0.000	0.001	-0.005	0.003	0.007**
		(0.051)	(0.047)	(0.084)	(0.008)	(0.004)	(0.011)	(0.007)	(0.005)	(0.005)	(0.002)	(0.003)
Observations		3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618
R-squared		0.681	0.524	0.624	0.565	0.722	0.632	0.634	0.528	0.645	0.654	0.800

The first block of each panel in this table reports the coefficients and standard errors (in parentheses) from estimating Eq. (3). An observation is a joiner and VC pair cross time, where time has been collapsed into two periods: pre- and post-PIR adoption in the VC's home state. The dependent variables correspond to the aggregate residuals from regressions of the outcome variables on year fixed effects, differential trends across the home states of VCs, and fixed effects at the level of the home state of the VC, which are then collapsed to two observations per joiner and VC pair: before and after the home state of the VC adopts PIR. PIR is an indicator that equals one after the home state of the VC adopts PIR via UPIA enactment. The second block of each panel in this table reports OLS estimates of Eq. (2) on the two-period panel (i.e., pre and post for every pair). The third block of each panel in this table reports IV estimates of Eq. (2) in the two-period panel, where I instrument Post using PIR. The event window includes all observations from joiner and VC pairs for which the VC's home state adopted PIR within the sample period, and corresponds to 29 years before and 16 years after the adoption of PIR in the home state of the VC. Panel A restricts the sample to joiners and portfolio companies that are located out of the home state of the VC. Panel B restricts the data to joiners and portfolio companies that are located out of the home state of the VC and are also not located in states that coincidentally passed PIR at the same time as the home state of the VC (coincidental states). Standard errors are heteroskedasticity robust and clustered at the home state of the VC level throughout.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.