Herding in the Market for Startup Acquisitions*

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Abstract

We document and quantify herding effects in the market for startup acquisitions, examining international acquisitions. Analyzing a sample of 5,725 Israeli venture-backed startups, we implement a machine learning algorithm to generate dyads of technologically similar companies. Difference-in-differences and instrumental variable models show that the acquisition of a startup by a foreign company increases the chances that its peer is also acquired by a foreign company by 61%. Instead, the effect is null when an initial acquisition is enacted by an Israeli firm. Consistent with informational herding, we show that the reaction of foreign firms intensifies with the prominence of an initial acquisition. Additionally, the less informed foreign acquirers respond more strongly to prominent acquisitions than to non-prominent acquisitions of Israeli startups, relative to the better informed. We further show that Israeli firms minimally react to the foreign acquisition of Israeli startups. Finally, the analysis of VC reactions and startup sales prices confirms an increase in the foreign demand for Israeli startups, following an initial acquisition.

Keywords: *Entrepreneurship*, *Herding*, *Acquisitions*, *Venture Capital*

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"Israel has become a global powerhouse in automotive and mobility technology, building on the success of such standouts as Waze and Mobileye."

—Mike Granoff, managing director of Maniv Mobility

1 Introduction

In 2013, Google acquired social mapping company Waze for \$1.3 billion dollars, making it the most lucrative exit for an Israeli startup at the time (Teig, 2013). After this acquisition, the panorama for Israeli startups in the mobility space changed substantively (Frenkel, 2020). Apple bought car-sensor company PrimeSense for \$300 million, Intel acquired Mobileye for \$15 billion, and Lyft announced a joint venture with the company Gett. According to anecdotal accounts, the acquisition of Waze opened a new spectrum of opportunities for Israeli mobility startups by attracting the attention of other foreign acquirers. This paper asks whether such initial acquisitions induce imitation by other potential acquirers, thereby improving acquisition prospects for startups in a given entrepreneurial ecosystem. We address this question using international acquisitions as an empirical context.

Firms are influenced by and imitate the behavior of their peers (Krieger, 2021). The theoretical literature has identified several sources of herding (imitation). For instance, information cascade models have focused on herd behavior triggered by informational externalities (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1992). These arise when an entity imitates the action of its predecessor, because relying on the informative content of this action is more convenient than following one's own private signal. Scharfstein and Stein (1990) explain herd behavior in the context of a principal-agent model, where agents are rewarded for convincing their principals that they are right. Other herding models have focused, instead, on complementarities, wherein an entity imitates the behavior of others because some actions are more worthwhile when others perform them as well (Becker, 1991). Despite the abundance of herding theories, empirical investigations remain sparse (Welch, 2000).

We examine herding effects in the market for startup acquisitions. While these transactions represent the prevalent exit mode for startups (Hellmann, 2006; Catalini et al., 2019), they are fraught with uncertainties (Hellmann, 2002; Higgins and Rodriguez, 2006; Benson and Ziedonis, 2010), and often prevent acquiring firms from deriving positive returns (Andrade et al., 2001). Firms in this market may imitate their predecessors to cope with these uncertainties, but also because the initial acquisition of a startup may generate positive payoff externalities. While this is a compelling hypothesis, it also possible that firms refrain from imitation to the extent that there is a scarcity of suitable startup targets. Firms may not follow the example of an initial acquirer due to a depletion of opportunities, a surge in the targets' price, or to avoid exacerbating competition.

To study these issues, we employ data on 5,725 Israeli startups that obtained financing between 2002 and 2019. Our rich data allow a full-fledged analysis of herding effects. We not only observe whether startups are acquired, but also their sales price, the financing amount they raised, and investor features. Israel is an ideal empirical setting for our analysis. The country produces technologies that are relevant for domestic and foreign incumbents alike. As such, demand for Israeli startups is fueled by both domestic and foreign firms. To the extent that opportunities in a given ecosystem are more uncertain for foreign than for domestic firms for geographical and/or cultural reasons, herding should be more relevant for the former than for the latter category of firms.[1] Accordingly, our analyses will primarily evaluate whether and how the initial acquisition of an Israeli startup by a foreign firm stimulates the demand for Israeli startups by other foreign firms, comparing their reaction to that of domestic firms.

Using descriptions of the startups and their technologies, we implement a machine learning algorithm to generate dyads of companies developing similar technologies. This is a fundamental step in our analysis given that herding among acquirers is more relevant if the technologies their target startups develop are similar. Building on this analysis, we implement a difference-

[1] Israel represents a unique entrepreneurial ecosystem with distinct characteristics relative to those in the US, Europe, and Far East Asia (Bresnahan et al., 2001). While some firms from these geographical areas have established R&D centers in Israel, somewhat reducing geographical distance, the cultural gap between Israeli startups and foreign incumbents remains wide (Senor and Singer, 2011). A report by the Israel Venture Capital Research Center reveals that several US companies tend to regard Israel as a "residual" market, acquiring its companies after having scouted opportunities in the US (IVC Research Center, 2019). For instance, Tom Leighton, CEO of Akamai, is quoted as saying "From the Technology point of view Israel is the most interesting place in the world *after* Silicon Valley."

in-differences approach, comparing over time the exit outcomes of startups whose peers were acquired by a foreign firm to the outcomes of control startups whose peers did not experience such an exit. These controls are randomly chosen outside of the treated startups' sectors of operation. We saturate the model with a wide array of fixed effects, including fixed effects for each dyad, subsector-by-year, and group of treated and control startups.

We find that those startups whose technologically similar peers were acquired by a foreign firm experience a subsequent 0.36 percentage point increase in the probability of being acquired by a foreign firm in a given year, relative to the control group. This is equivalent to a 61% increase in the mean. A complementary event study detects no pre-trends. These findings are confirmed when, following Freyaldenhoven et al. (2019), we implement an instrumental variables approach to address the concern that a dyadic startup's time varying behavior –such as the development of a successful technology– may affect the likelihoods that the startup and its peer are acquired by a foreign company. This approach consists of instrumenting a time-varying control with the lead(s) of the treatment to remove the effect of the confounding factors of interest. Accordingly, we instrument an observed startup's patenting with the first lead of our acquisition treatment event. Reassuringly, the resulting treatment effect on the probability that a startup is acquired by a foreign company in a given year does not change. Consistent with the idea that opportunities in a given ecosystem are more uncertain for foreign than for domestic firms, we additionally find that the treatment effect on the probability that a startup is acquired by an Israeli company is 0.1 percentage points only, or a 29% increase relative to the outcome mean.

We provide several additional findings that shine light on the mechanisms behind these herding effects. First, we show that these effects increase with technology similarity between two startups in a dyad. Indeed, when we adopt more stringent criteria for selecting peers developing similar technologies, we find that startups whose peers are acquired by a foreign company experience a 85% increase in their likelihood of going through a similar exit, relative to the outcome mean. This is a considerably larger effect than the baseline effect described earlier. Conversely, the effect on acquisitions by Israeli companies remains considerably smaller. These results suggest that the benefits from imitation increase with the technology similarity between an initially acquired startup and a firm's potential target, and are especially large for those acquirers for whom uncertainties are relatively more severe. Second, we show that while foreign acquirers react to the acquisition of Israeli startups by other foreign firms, they are not responsive to acquisitions by Israeli firms. This result is consistent with herding effects being intensified when potential acquirers share similar backgrounds and preferences. Third, we show that herding effects strengthen when the initial acquisition is undertaken by a prominent foreign acquirer and when such an acquisition has received widespread attention in the news. Fourth, we provide evidence that the less informed foreign acquirers -namely, non-US acquirers and foreign acquirers without an R&D center in Israel- respond more strongly to prominent acquisitions than to non-prominent acquisitions of Israeli startups, relative to the better informed foreign acquirers. This result provides further support to the conjecture that herd behavior among foreign acquirers is at least in part triggered by information frictions. Finally, being associated with an initial prominent acquisitions is more impactful than being associated with subsequent acquisitions. This suggests that prominent acquisitions of Israeli startups trigger immediate herding effects, which dissipate over time once additional sources of information become available or the availability of suitable targets declines.

There are three alternative channels to herding in the startup acquisition market. One is that an initial acquisition spurs venture capitalists' (VCs) activities that enhance their portfolio startups' value, making these companies more attractive to foreign acquirers. However, we show that investors do not invest larger amounts in their companies after the technologically similar peers have been acquired. Additionally, we could be capturing supply *and not* demand effects to the extent that an initial acquisition leads to more startups seeking acquisition opportunities. However, we show that startups whose peers were acquired by a foreign company sell at a higher price than their controls. Had our results been explained *solely* by supply effects, we would have observed a decline and not an increase in the sales price of treated startups. Finally, the acquisition of a startup by a foreign firm could be followed by further acquisitions just because competitors are after the same complementary assets, regardless of mimicry. For instance, it is possible that firms decide to join an acquisition wave and simultaneously acquire social mapping companies, like Waze, because their assets have become valuable. However, our effects hold and become stronger after replacing subsector by year fixed effects with technology keyword by year fixed effects, noting that there are approximately 700 keywords describing our startup technologies.

Our results point to an increase in the demand for *Israeli* startups by foreign firms after an initial acquisition. Yet, it is possible that the herding effects are triggered by firms responding to certain technological opportunities, regardless of the location in which they are developed. To investigate this issue, we examine whether the acquisition of an Israeli company by a US acquirer positively affects the acquisition opportunities of US startups developing similar technologies as the Israeli company. We find that after an Israeli startup is acquired, US startups developing similar technologies do not improve their acquisition chances relative to US startups that produce dissimilar technologies. This result provides a strong indication that our herding effects are driven by firms reacting to opportunities in a specific ecosystem. Moreover, it provides further evidence that acquisition waves do not drive our results.

Our paper provides an important contribution towards understanding the determinants of startup acquisitions. While firm quality (Catalini et al., 2019), founder turnover (Ewens and Marx, 2017; Conti and Graham, 2020), proximity to potential acquirers (Conti and Guzman, 2021), VC characteristics (Hochberg et al., 2007; Ewens and Rhodes-Kropf, 2015; Korteweg and Sorensen, 2017), and business cycles (Nanda and Rhodes-Kropf, 2013) have been shown to impact startup acquisitions, the focus of our study is on herding effects. To the best of our knowledge, this is the first paper providing evidence that firms imitate the acquisition behavior of their predecessors, particularly when uncertainty over their startup targets is high. With this last result, we also contribute to the literature examining information frictions inherent in an investor-investee relationship involving startups (Conti et al., 2013a,b; Hsu and Ziedonis, 2013; Howell, 2020). Our specific focus is on how firms cope with uncertainties in the context of the startups' exit market. In this context, we advance the literature that has investigated the certification role played by VCs (Hsu, 2004), especially in initial public offerings (IPOs) (Megginson and Weiss, 1991), and the effect of patent applications in revealing private information on a startup's technology (Chondrakis et al., 2019).

The following section describes the data and the machine learning approach for generating dyads of technologically related startups. Section 3 describes our empirical models, while Section 4 presents the results. Section 5 concludes.

2 Data

2.1 Database description

The data used in this paper is assembled from a variety of sources. The main dataset is constructed from the Israeli startup database available from the Israel Venture Capital (IVC) Research Center. Similar to the US Venture Capital Association, IVC collects detailed information on Israeli startups' financing rounds and participating investors, founding location and date, technology, sector and subsector of operation, and exit outcomes (acquisitions and IPOs). Previous research has extensively used this database and validated it as an accurate representation of the Israeli high-tech startup ecosystem (Avnimelech and Teubal, 2006; Conti et al., 2013a; Conti, 2018; Conti and Guzman, 2021).[2] From the IVC dataset we retained the population of 5,725 Israeli startups that raised a financing round between 2002 and 2019 and were founded between 1998 and 2018. We consulted secondary sources to determine the location of the investors, including the location of their principal business, and their typology whenever it was missing. This supplementary information came primarily from investors' descriptions reported on their and the Bloomberg websites, as well as individuals' LinkedIn profiles. We enriched this dataset further with information on the startup acquirers, available from Start-Up Nation Central. We used this latter source to distinguish acquirers according to whether they are Israeli or foreign and, in the case of foreign acquirers, according to whether or not their headquarters are in the US. Finally, we collected information on the patents that startups applied for with the US Patent and Trademark Office (USPTO).

Table 1 reports descriptive statistics that shed light on the characteristics of our sample companies. As shown, Israeli startups operate in the following sectors: cleantech, communications, IT

[2] Upon inspection, this dataset has, for instance, a considerably better coverage of Israeli startup activities than Crunchbase.

& enterprise software, Internet, life sciences, semiconductors, as well as miscellaneous technologies.[3] Not surprisingly, the majority of the startups (61%) are active in the communications, IT & enterprise software, and internet sectors, reflecting Israel's comparative advantage in these sectors.

The average startup in our sample raised a total of $8.06 million during the period we observe, although the distribution is skewed as illustrated by the low median value ($0.7 million). The startup financing was raised over an average of 1.72 rounds. IVC classifies startup investors into VCs, private equity firms, banks, advisory & management companies, technology firms, government, and private investors. Thirty-eight percent of the startups raised VC funds and 16% received financing from US VCs.

Because we only have information regarding the amount startups raised in each round and the participating investors, and not information regarding the amount invested by each investor, we make the assumption that when a US investor invests in a given round that investor represents the largest contributor to that round. This is a reasonable assumption given that US investors possess greater resources than Israeli investors (Conti, 2018). As reported in the table, the average amount of funds a startup received from US investors is $5.15 million, and the average amount of US VC is $3.55 million.

The average number of patents a startup applied for with the USPTO is 1.23, with a minimum of zero and a maximum of 191. Fourteen percent of startups experienced an exit through either an IPO or an acquisition (or, in rare cases, a merger). The percentage of startups that went public via an IPO is considerably smaller (2%) than the percentage of those that were acquired (12%). This is consistent with the distribution of startup outcomes found by Catalini et al. (2019). Moreover, given that the focus of this paper is on the market for startup acquisitions, we classified approximately 10 public companies that were subsequently acquired as "acquired" startups. Finally, 8% of the startups were acquired by a foreign company, and particularly 6% were acquired by a US company.

⟨ Insert Table 1 about here ⟩

[3] Miscellaneous technologies typically display strong links with those developed in the communications and IT & enterprise software sectors.

2.2 Construction of startup dyads

To assess herding effects, we constructed dyads of companies operating in closely related technology areas. This is because the mechanism we analyze is especially relevant if the technologies the startups develop are similar. The process consists of two steps. To start, we considered the keywords that IVC uses to describe a startup's technology. As an example, the technology that the company Waze develops is described by the following keywords: Mobile GPS, Social Mobile Application, Location Based Services, Social Commuting, and Geogaming. These keywords are available for approximately 74% of the sample companies. In order to keep the 26% of the companies that were not originally assigned any keywords in our sample, we implemented a machine learning algorithm to assign each company a set of technology keywords. This algorithm exploits the richness of the IVC data, which includes generic company descriptions, as well as in-depth descriptions of the companies' technologies and their targeted markets. Importantly, these descriptions, along with the keywords, tend to remain unchanged over time. Thus, we can make the assumption that they reflect the technologies and products that the companies had started developing at the time they were founded. The details of the algorithm are provided in Section A.1 of the Appendix. As an output, the algorithm assigns each company a set of keywords. Importantly, those companies whose technology was originally described by a set of keywords are re-assigned a new set.

Reassuringly, the algorithm achieves a false positive rate of only 1%. We further assess the accuracy of this method by generating all possible dyads of startups and computing the following similarity measure: $\frac{NSharedTags_{ij}}{min(NTags_i, NTags_j)}$ between companies i and j in a given dyad, that is, the ratio of the number of technology keywords that i and j share to the minimum number of keywords between i and j. As shown at the top of Figure 1 from left to right, the mean value of the similarity measure is largest for paired startups that belong to the same subsector[4] and progressively declines

[4]For example, the communications sector encompasses the following subsectors: broadband access, broadcast, enterprise networking, home networking, mobile applications, mobile infrastructure, NGN & convergence, optical networking, security, telecom applications, VoIP & IP telephony, wireless applications, and wireless infrastructure. We report the entire list of subsectors in Table A1 of the Appendix.

for paired startups operating in the same sector and for those assigned to the same broad area. At the bottom of Figure 1, we report the results from an alternative test. Here, we assess whether the similarity measure is greater the larger the number of investors the startups in a dyad share. To the extent that investors specialize in given sectors (Gompers et al., 2009), sharing investors should be indicative of producing similar technologies. The figure displays a steady increase in the mean value of the similarity measure as the number of investors the startups in a dyad have in common rises.

⟨ Insert Figure 1 about here ⟩

Having assigned each company a set of keywords, the second step consists of defining dyads of companies developing similar technologies. These are all dyads of startups operating in the same broad technology areas and sharing at least three technology keywords. The technology areas are: cleantech, life sciences, internet, and remaining sectors. The remaining sectors category includes the following: communications, IT & enterprise software, semiconductors, and miscellaneous technologies. The reason for incorporating the latter sectors into a unique broad area is that, having inspected the keywords IVC assigns to the startups in order to describe their technology, we realized that the startups operating in these sectors would often share at least one keyword.[5]

Finally, building on the two steps just described, we determined: i) which startup in a dyad should be the "observed" startup, that is, the company whose exit outcome will be evaluated, and ii) which startup should represent the "peer", that is, the company that will be the source of the analyzed treatment. To do so, we randomly classified dyadic startups as either "observed" or "peer" companies.

3 Empirical strategy

3.1 Empirical specification and identification

We examine how the acquisition of an Israeli startup by a foreign firm affects the likelihood that other technologically similar Israeli startups will be acquired, especially by foreign companies.

[5] Internet startups rarely share keywords with startups in communications, IT & enterprise software.

We adopt a difference-in-differences approach and compare, over time, an observed startup whose peer was acquired by a foreign firm to a set of control startups whose peers did not experience such an acquisition event. To build the control group, we randomly selected approximately ten companies for each startup treated with a foreign acquisition i) from the set of non-treated companies established during the same year as the treated startup, but ii) operating in a different sector. With criterion i) we ensure that we are comparing startups facing similar macroeconomic trends at founding and going through a similar life cycle. The rationale behind criterion ii) is that we want the effect of a given acquisition treatment to be as small as possible for the control group.[6]

The goal of our difference-in-differences approach is to compare two sets of startups at risk of being acquired, one of which had the peer acquired. We, therefore, exclude from the sample instances where a peer was acquired before the associated startup is founded and those startups -either in the treatment or in the control group- that experienced an exit before the associated treatment occurred. As we mentioned earlier, our main analyses focus on dyads wherein the observed startups share at least three technology keywords with their peers. This is to ensure that we examine dyads of startups producing similar technologies. However, our analyses are robust to, for instance, examining startups that share at least two technology keywords with their peer. Estimation is based on Eq. (1):

$$\begin{aligned} Y_{ijt} = {} & \alpha PostAcquisition_{gt} + \beta PostAcquisition_{gt} x Peer\,Acquired\,by\,Foreign\,Firm_i + \\ & + \omega_{ij} + \psi_g + \mu_{it} + \gamma_{jt} + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

Y_{ijt} is defined as the probability that startup i, paired with startup j, is acquired in year t. We examine variants of this outcome, specifically focusing on acquisitions by foreign companies, which we contrast to acquisitions by domestic companies. The $Peer\,Acquired\,by\,Foreign\,Firm_i$ indicator -our treatment- takes a value of one if peer j of startup i is acquired by a foreign firm and zero otherwise. As the effect of this indicator is absorbed by our fixed effects, we only include it in the

[6]Ideally, the effect of an acquisition event should be zero for the control group of startups (Angrist and Pischke, 2008). While this condition may only be partially satisfied in our context, given Israel's small size, our estimates represent a lower bound.

interaction with $PostAcquisition_{gt}$. The variable $PostAcquisition_{gt}$ is a time varying binary indicator that becomes one for all the startups in a treated-control group g after the peer j of a treated startup is acquired by a foreign firm. This indicator captures a time trend common to both the treated startups and their controls. The coefficient of interest is β, which is associated with the interaction between $Peer\,Acquired\,by\,Foreign\,Firm_i$ and $PostAcquisition_{gt}$. This coefficient measures the average increase in the likelihood that a startup is acquired in year t after its peer is acquired by a foreign company relative to the control group. A β greater than zero would be consistent with heard behavior among acquirers, to the extent that -all else equal- the initial acquisition by a foreign company induces other firms to expand their demand for Israeli startups developing similar technologies to the initial acquiree. We observe each startup in a given treated-control group g during the period starting five years before a given acquisition event and ending ten years after. Modifying this temporal cutoff does not change our results.

The empirical concern here is that the exposure to a given acquisition event is unlikely to be random. Such an exposure may be correlated with factors, including characteristics of an observed startup and its peer, as well as technology trends, that could affect the outcome in Eq. (1). To address this concern, our main specification is saturated with a battery of fixed effects. In particular, ω_{ij} denotes the fixed effect for the ij dyad. The ψ_g represents the fixed effect for group g encompassing a treated startup and its controls. Moreover, μ_{it} is a i's subsector-by-year fixed effect, γ_{jt} is a j's subsector-by-year fixed effect, while ε_{ijt} is an idiosyncratic error term.

The inclusion of ω_{ij} fully controls for fixed differences between ij dyads. Moreover, ψ_g absorbs time-invariant heterogeneity across treated-control groups gs. The fixed effects μ_{it} and γ_{jt} account for technology shocks that may correlate with the acquisition of an observed startup or its peer. We have a fine-grained list of subsectors, which we report in Table A1. [7]

[7] In a more conservative specification, whose results we present in Table A5, we show that our main effects minimally change after we control for time varying aspects of i, j, and the dyad ij. We omit these controls in our main specifications as they may be endogenous given that startups may implement certain strategies specifically to achieve an exit.

3.1.1 Instrumental variable approach

We complement the model of Eq. 1 with an IV approach. One possible concern with our difference-in-differences model is that despite the fine-grained list of fixed effects for which we control, the time varying behavior of an observed startup or its peer may affect the likelihoods that the companies are acquired. Even if we observed no significant pre-trends, pre-trends could be present but undetected due to limited statistical power. One worry, for instance, is that the development of a successful technology in year t by either observed startup i or peer j could increase the likelihood that the technology developer is acquired. Moreover, it could enhance or hamper the chances that the other company is acquired, provided that i's technology is a complement to or a substitute for j's technology. These mechanisms could systematically vary across dyads, depending on whether they belong to the treated or to the control group. To address this concern, we implement an instrumental variables (IV) approach following Freyaldenhoven et al. (2019), which we nest into the empirical model of Eq. (1).[8]

This approach consists of instrumenting a time-varying control with the lead(s) of the treatment to remove the effect of the confounding factor of interest. The approach requires a time-varying covariate that i) is likely to be affected by the confounder, but that ii) is not affected directly by the treatment. The covariate is employed in a two-stage least squares (2SLS) estimator because including it as a control in a standard OLS model would correct for the confounder only if the effects of the confounder on the control and on the outcomes were exactly parallel. We employ the cumulative likelihood that a startup will have applied for a granted patent with the USPTO by t as the time-varying covariate. We instrument this variable with the first lead of the interaction between $PostAcquisition_{gt}$ and $PeerAcquiredbyForeignFirm_i$. There is a positive correlation between a company's technological developments and its patent output (Aghion et al., 2013). Moreover, j's technology developments that could be correlated with the error term should be reflected in i's patent response. Yet, the acquisition of a technologically similar peer j is unlikely to immediately

[8]This approach is widely adopted in the economics and finance literatures. See, for example, Jakobsen et al. (2020) and Eaton et al. (2020).

cause a patent strategy reaction by the observed startup *i* as there are non-systematic lags between the moment a technology is developed and the moment a patent is applied for.

3.2 Descriptive statistics

Our main sample is composed of 133,198 startup dyads and 1,191,267 dyad-year observations. These dyads are formed by 5,402 "observed startups" (whose outcomes will be evaluated) which are matched with 5,495 unique technologically similar "peers" (the treatment source). Table 2a and Table 2b report summary statistics at the dyad and dyad-year levels, respectively. In both tables, we distinguish dyads according to whether an observed startup *i* in dyad *ij* is treated with the foreign acquisition of its peer *j*.

Although these tables only report descriptive statistics, they offer a first glance into the herding mechanism that we plan to investigate: namely, the initial acquisition of an Israeli startup by a foreign firm could attract other potential acquirers, especially foreign companies, thereby improving subsequent acquisition opportunities for the remaining Israeli startups. For instance, Table 2a shows that the proportion of observed startups that experience an exit (IPO or acquisition) is 14% if such startups are matched with a peer that was acquired by a foreign firm (*Treatment=1*), while it is 9% if the startups' peers are not acquired by a foreign firm (*Treatment=0*). This gap widens once we consider acquisitions only. Exploring this exit mode further, we note that the proportion of observed startups that are acquired by a foreign company is 8.9% in the treated group and 4.9% in the non-treated group. This difference of 4 percentage points is statistically significant and it is mostly driven by US firms' acquisitions of Israeli startups. The difference between the treated and non-treated group is instead reduced to 1.5 percentage points when we examine acquisitions by Israeli firms as an exit outcome. We additionally note that, conditioning on those observed startups that were acquired and for which we have sales price information, the price is higher for startups in the treated group than for those in the control group. Finally, observed startups in the treated group raise more funds and more US funds than the corresponding startups in the control group. The summary statistics at the dyad-year level reported in Table 2b are consistent with the dyad-level statistics just discussed.

⟨ Insert Table 2 about here ⟩

4 Empirical results: Herding in the market for startup acquisitions

We next proceed to present our empirical results on herding in the market for startup acquisitions. Section 4.1 describes the main difference-in-differences and IV results, Section 4.2 sheds light on the mechanisms driving our results, Section 4.3 discusses possible alternative channels to herding, and Section 4.4 presents miscellaneous robustness checks.

4.1 Main results

Regression estimates for the effect of a peer that is acquired by a foreign firm are reported in Table 3 using variants of Eq. (1). The displayed models include fixed effects for i) dyad ij, ii) treated-control group g, and iii) subsector-by-year. We double cluster standard errors by group g and year t. Other clustering methods, including clustering by group g, observed startup i, and peer j, produce very similar standard errors. We begin by assessing how the acquisition of a peer j in dyad ij generally affects a startup's likelihood of exiting, via either an acquisition or an initial public offering (IPO). The results are reported in column 1. The positive coefficient of $PostAcquisition_{gt}$ indicates the existence of a common trend. After the acquisition of a peer, the likelihood of experiencing a liquidity event in t increases by 1.9 percentage points, on average, for the control startups, representing a 179% increment relative to the mean. This increase follows mechanically from the condition we have established that the startups in a given treated-control group g can only experience a liquidity event after the peer j of the treated startup is acquired by a foreign firm.

Our coefficient of interest, the one associated with the interaction between $PostAcquisition_{gt}$ and $PeerAcquired\ by ForeignFirm_i$, is positive. Its magnitude indicates that startups whose technologically related peers were acquired by a foreign firms improve their likelihood of experiencing an exit -post-treatment- by an additional 0.43 percentage points relative to the control group. This effect is significant at the one percent level, and economically relevant given that it corresponds to a 40% increase in the outcome mean.

In column 2, we zoom in on startup acquisitions and assess the probability that startup i is acquired in t. As shown, the exit results just discussed are driven by acquisition events. In fact, treated startups become 0.47 percentage points more likely to be acquired in a given year compared to the control group, after the treatment. This effect is equivalent to a 49% increase in the outcome mean. Overall, these findings provide a strong indication that -all else equal- the initial acquisition of an Israeli startup induces further acquisitions, thereby improving the overall acquisition prospects for Israeli startups.

We next examine the reaction of foreign acquirers and contrast it to the one by domestic acquirers. For this purpose, we decompose the observed startups' acquisitions according to whether the acquirers are foreign or domestic. Our intuition is that, because information problems are more severe for foreign than for domestic acquirers due to geographical and/or cultural distance, herding effects should be stronger for the former category of acquirers. We thus modify the dependent variable in Eq. (1) by generating the following two additional outcomes. The first is the probability that startup i, paired with startup j, is acquired by a foreign company in year t. The second is the probability that startup i is acquired by an Israeli company. The results are reported in columns 3 and 4 of Table 3. The common time trend is the same for the two outcomes. Regardless of whether the examined outcome is an acquisition by a foreign firm (column 3) or an acquisition by an Israeli firm (column 4), untreated startups increase their likelihood of achieving these exits by approximately 178% post-treatment. Moving to the interaction effects, column 3 shows that, after a peer j is acquired by a foreign company, startup i experiences an additional 0.37 percentage point increase in the likelihood of being acquired by a foreign firm relative to the control group, which corresponds to a 61% increment in the outcome mean. In contrast, the coefficient of the interaction between $PostAcquisition_{gt}$ and $Peer\,Acquired\,by\,Foreign\,Firm_i$ on the probability that a startup is acquired by an Israeli firm (column 4) is much lower, 0.11 percentage points, corresponding to a 29% increase in the examined outcome.

⟨ Insert Table 3 about here ⟩

Figure 2 next examines herding effects within an event study framework. To do so, we modify Eq. (1) by substituting the $PostAcquisition_{gt}$ indicator with binary variables for each of the pre- and post-treatment years. This specification allows us to compare the outcomes of a startup whose peer was acquired by a foreign firm to the control group, in each year before and after the acquisition event. We control for the full set of fixed effects listed in Eq. (1). We plot the difference-in-differences coefficient estimates for the probability that a startup is acquired, distinguishing between acquisitions by foreign (top) and Israeli (bottom) firms. We observe three important patterns. First, there are no significant pre-trends, which suggests that our approach is able to account for selection into treatment. Second, the top figure displays a large and immediate increase in the probability that startup i is acquired by a foreign company starting from year 0.[9] The effects remain large up until year +4 and decline afterwards, suggesting that alternative information sources may become available over time or that the demand by foreign firms may progressively fade. Finally, when examining the probability that a startup is acquired by an Israeli firm at the bottom of Figure 2, we observe that the treatment effects during and after the treatment year are considerably smaller than those reported at the top of Figure 2 and noisier.

⟨ Insert Figure 2 about here ⟩

We suggested that the herding behavior we observe among foreign acquirers could be motivated by information problems. Yet, an alternative interpretation may be that foreign firms are more responsive to the initial acquisition of an Israeli startup than their domestic counterparts because they are relatively more endowed. To assess the relevance of this alternative explanation, we distinguish between whether i is acquired by a large foreign company or by a smaller one. The rationale is that if endowment differences were the sole driver of our findings, then the latter would be entirely driven by larger foreign acquirers. Large firms are those such as Dell, General Electrics, IBM, Intel, Oracle, and Cisco, that are in the top quartile for their size distribution. The results

[9] The steep increase we detect in year 0 is likely due to the fact that we observe an actual acquisition date. However, acquisitions are typically announced to the public a few months earlier.

of this test are reported in Table A2. Although treated startups are relatively more likely to be acquired by a large acquirer than by a smaller one, the effect of the treatment on the likelihood that a startup is subsequently acquired by a smaller foreign firm remains sizable. After a peer is acquired by a foreign firm, the associated observed startup becomes 0.22 percentage points more likely to be acquired by a smaller foreign firm relative to the control group, equivalent to a 54% increase in the mean. This finding supports our conjecture that the herding effects we observe are, at least in part, explained by firms coping with their limited information on potential targets.

Next, we move to our IV approach to further validate the results. While we did not detect significant pre-trends, we want to exclude any concern that our estimates are confounded by unobserved *time-varying* startup characteristics. For this purpose, we employ the IV estimator proposed by Freyaldenhoven et al. (2019) and described in Section 3. Thus, we estimate a 2SLS model and instrument the cumulative likelihood that a startup will have applied for a granted patent with the USPTO by t with the first lead of the interaction between $PostAcquisition_{gt}$ and $PeerAcquired\,by\,Foreign\,Firm_i$. The IV results are reported in Table 4 and in Figure A1. As before, we include fixed effects for dyad ij, treated-control group g, and subsector-by-year.

The reported estimates in Table 4 confirm our earlier findings. In particular, after a peer is acquired by a foreign firm, the associated observed startup becomes 0.4 percentage points more likely to be acquired by a foreign firm in a given year, relative to the control group (column 1 of Table 4). This point estimate represents a 61% increment in the mean outcome, the same increment as the one obtained from estimating Eq. (1). As shown in column 2, both the magnitude and the significance of the effect associated with the interaction between $PostAcquisition_{gt}$ and $PeerAcquired\,by\,Foreign\,Firm_i$ on the likelihood that a startup is acquired by an Israeli firm in t are lower than those reported in column 1. After the treatment, treated startups become 0.096 percentage points more likely to be acquired by an Israeli firm in a given year relative to the control group. This relative increase is equivalent to a 24% increment in the outcome mean. Finally, the event studies reported in Figure A1 continue to show similar patterns as those depicted in Figure 3.

⟨ Insert Table 4 about here ⟩

4.2 Mechanisms

Having shown that startups improve their chances of being acquired, especially by foreign firms, after their peers have been acquired by foreign companies, this section delves into the channels through which herding among acquiring firms operates. We start by assessing the role of the technological similarity between two target startups in shaping herding behavior among acquirers. It is plausible that the positive externalities generated by an initial acquisition are larger the more similar the technologies two startups produce. To explore this conjecture, we adopt a more stringent criterion for defining dyads of technologically similar startups. Specifically, we impose not only that a dyad ij shares at least three technology keywords, but also that at least one of those keywords is among the three most relevant for describing i's and j's technologies according to our machine learning algorithm.[10]

The results from estimating Eq. (1) are reported in Table 5. After their peers have been acquired by a foreign company, treated startups increase their likelihood of achieving an exit (column 1) and of being acquired (column 2) by 0.55 and 0.65 percentage points, respectively, relative to the control group. These effects are larger than those reported in Table 3 given that they represent a 52% and a 71% increase in the outcome means, respectively. Moreover, the effect intensifies in column 3, where the analyzed outcome is the likelihood that a startup is acquired by a foreign company in t. Here, the coefficient associated with the interaction between $PostAcquisition_{gt}$ and $Peer Acquired by Foreign Firm_i$, implies that -after a peer is acquired by a foreign company-treated startups experience an additional 0.48 percentage point increase in their likelihood of being acquired by a foreign company relative to the control group, equivalent to an average 84% increase in the unconditional probability. Reassuringly, this effect remains similar (85%) in column 4, where we adopt a conservative approach and substitute subsector times year fixed effects with technology keywords times year fixed effects.[11] As we mention in Appendix A.1, there are more

[10] Refer to Appendix A.1 for further details.

[11] The keywords we use are the ones ranking first for importance in terms of describing a company's technology.

than 700 keywords describing the startup technologies and, thus, they allow us to more precisely control for technology trends. Thus, this last finding provides a strong indication that possible acquisition waves following technology shocks are unlikely to bias our effects upward.

The results reported in column 5 for the likelihood that an Israeli startups is acquired by a domestic company show that the coefficient associated with the interaction between $PostAcquisition_{gt}$ and $Peer Acquired by Foreign Firm_i$ continues to be smaller both in absolute and relative terms compared to the coefficients reported in columns 3 and 4. Moreover, the magnitude of the coefficient declines by 23% in column 6, once we add technology keywords by year fixed effects. The reported coefficient in this column implies that startups whose peer was acquired by a foreign company experience an average 41% increase in their likelihood of being acquired by a domestic company relative to the unconditional probability. Overall, these results are consistent with a herding mechanism whereby the value of an initial acquisition by a foreign firm increases with the technology similarity between two startups in a dyad and appears to be largest for the least informed potential acquirers.

⟨ Insert Table 5 about here ⟩

Next, we focus on foreign acquirers and evaluate the type of predecessors they are more likely to imitate. It is plausible that foreign acquirers are more prone to follow the strategies of their foreign rather than their domestic predecessors to the extent that they trust or value the former predecessors relatively more. To verify this hypothesis, we modify Eq. (1) and substitute the *Peer Acquired by Foreign* $Firm_i$ indicator with a binary variable that takes the value of one if i's peer j is acquired by an Israeli firm and zero otherwise. We regenerate the treated-control groups gs adopting the same criteria as those listed in Section 3, except that this time the treatment of interest is the acquisition of a given peer j by an Israeli company. The results are reported in Table 6. Consistent with our conjecture, column 1 shows that, after a peer is acquired by an Israeli firm, the associated observed startup does not significantly improve its chances of being acquired by a foreign firm relative to the control group. The effect is not only statistically insignificant, but its magnitude is also very small.

⟨ Insert Table 6 about here ⟩

In our third analysis, we assess whether herding among foreign acquirers varies depending on how prominent the initial acquisition of a peer j by a foreign firm is. We define prominent acquisitions as those enacted by prominent acquirers. These acquirers are companies, such as Apple, Cisco, Google, IBM, and Oracle, which figure among the top acquirers in the IVC and Crunchbase datasets.[12] These are companies at the technology frontier and, thus, imitating their strategies may be relatively more valuable. We implement the analysis by modifying Eq. (1) and decomposing the $Peer Acquired by Foreign Firm_i$ variable into two indicators, respectively denoting prominent and less prominent acquisitions of Israeli startups by foreign companies. Similarly, we generated two $PostAcquisition_{gt}$ binary indicators: the first takes value one after a peer j is acquired by a prominent foreign firm and zero otherwise; the second becomes one after a peer j is acquired by a less prominent foreign firm. The results are reported in Table 7.

Column 1 shows that the coefficient of the interaction between $PostAcquisition_{gt}$ and the indicator for whether a peer was acquired by a prominent foreign acquirer is 51% larger than that associated with the interaction between $PostAcquisition_{gt}$ and the indicator for whether a peer was acquired by a less prominent foreign acquirer. The non-prominent acquisition of a peer has a significant impact, albeit relatively smaller, on the likelihood that a treated startup is acquired by a foreign company compared to the control group. This result suggests that the impact of foreign acquisitions transcends the role of prominence.

In column 2, we refine the notion of prominent acquisitions and retain only those that received widespread media attention and whose sales price is above the sector median for a given year. To measure media attention, we collected from LexisNexis news reports concerning the acquisition of a startup that were published between six months before and six months after the acquisition event. Building on these data, a prominent acquisition is considered to have received widespread media attention if the number of news reports mentioning it is above the sector median. As reported, the gap between the difference-in-differences estimates associated with prominent and less-prominent

[12]The complete list of prominent acquirers is provided in Appendix Table A3.

foreign acquisitions increases to 143%. Overall, these results indicate that herding among foreign acquirers intensifies with the prominence of an initial acquisition.

⟨ Insert Table 7 about here ⟩

Delving deeper into our prominent acquisition results, we examine whether there is any difference between less informed and better informed foreign potential acquirers in the way they react to the prominence of an initial acquisition. Accordingly, we distinguish between the likelihood that a startup is acquired by a US acquirer and the likelihood that it is acquired by either a European or an Asian acquirer. We make this distinction because US firms have stronger ties with the Israeli startup ecosystem than other foreign firms and, thus, they should be relatively more informed about acquisition opportunities in this ecosystem. In a similar vein, we distinguish between the likelihood that a startup is acquired by a foreign acquirer with an R&D center in Israel and the likelihood that it is acquired by a foreign acquirer without such an R&D center, under the assumption that the former acquirer is better informed than the latter. The results are reported in Table 8. We adopt the same definition of prominence as the one employed in column 2 of Table 7. As reported in column 1 of Table 8, a startup becomes 0.57 percentage points more likely to be acquired by a US firm as result of an initial prominent acquisition, while the increase is only 0.27 percentage points when the initial acquisition is less prominent. This 108% gap in effects widens to 300% when we instead examine the likelihood that a startup is acquired by either a European or an Asian firm (column 2). Similarly, the results in column 3 show that a startup becomes 0.18 percentage points more likely to be acquired by a foreign firm with an R&D center in Israel following an initial prominent acquisition, while the increment is only 0.1 percentage points when the initial acquisition is less prominent. The 81% difference in effects increases to 169%, when the outcome examined is the likelihood that a startup is acquired by a foreign firm with no R&D center in Israel (column 4). Overall, these results provide a strong indication that the less informed foreign acquirers respond more strongly to prominent acquisitions than to non-prominent acquisitions of Israeli startups by other foreign firms, relative to the better informed foreign acquirers.

⟨ Insert Table 8 about here ⟩

To conclude this section, we examine whether an observed startup's acquisition outcome is more sensitive to earlier or later foreign acquisitions of its technologically similar peers, and whether any reaction depends on the prominence of a given acquisition. An initial pioneer acquisition should matter more than subsequent acquisitions for at least two reasons. First, new sources of information may become available over time that reduce the rationale for herding (Bikhchandani et al., 1992). Second, as firms acquire Israeli startups, the remaining targets may be less appealing to potential acquirers. Building on our earlier findings regarding prominent acquisitions, we expect the effects of pioneer acquisitions to be amplified if they are enacted by prominent acquirers. To implement this analysis, we condition on those instances in which the peer j of a given startup i is acquired by a foreign company and rank these acquisition events from the earliest to the more recent. We then examine how i's chances of being acquired by a foreign company vary pre- and post-treatment, comparing earlier to more recent treatments and, moreover, contrasting prominent with less prominent treatments.

The results are reported in Figure 3. In Panel A, we plot the time coefficients pre and post the prominent acquisition of i's peer j by a foreign company, having distinguished between the earliest and the second acquisition of j. In line with our conjecture, we find that the earliest acquisition produces stronger effects than the more recent one. Panel B zooms in on the earliest foreign acquisitions, contrasting prominent with non-prominent acquisitions. Remarkably, the treatment effects of a pioneer (i.e. earliest) acquisition are greater than zero only if such an acquisition is prominent. A similar pattern as in Panel A is displayed in Panel C, where we contrast the earliest prominent acquisition of a peer j by a foreign company with the third of such events. Finally, Panel D compares the second to the third prominent acquisition of i's peers. Here, we continue to find that the earlier prominent acquisition of i's peer j by a foreign acquirer generates stronger effects than the more recent treatment, although the difference in effects is less pronounced. Overall, these results strongly suggest that prominent acquisitions of Israeli startups trigger immediate herding effects, which dissipate over time once the information value of an initial acquisition fades or the availability of suitable targets declines.

⟨ Insert Figure 3 about here ⟩

4.3 Alternative interpretations

Thus far, our findings support the existence of herding in the market for startup acquisitions, whereby firms -especially foreign ones- imitate the strategy of their predecessors and improve exit prospects for startups located in a given ecosystem. In this section, we discuss several additional tests that we implemented to address potential alternative explanations.

4.3.1 The role of intermediate investors

We begin by considering the reaction of intermediate investors to an initial acquisition event. The initial acquisition of a startup by a foreign company may attract the attention of investors, such as VCs, inducing them to increase the size of the investments they make in their portfolio startups. As a result, the quality of these startups would increase and so would their exit prospects, independently of acquiror mimicry. While our IV strategy should in principle rule out this alternative explanation, we evaluate more closely how investors react to the acquisition of Israeli startups by foreign firms. For this purpose, we estimate a modified version of Eq. (1), where the outcome becomes the yearly change in the natural logarithm of the cumulative amount of funds a startup raised by year t. The results are reported in Table 9. We control for the full set of fixed effects and cluster standard errors by treated-control group g and year t.

Column 1 of Table 9 shows that the $PostAcquisition_{gt}$ coefficient is negative and significant, indicating a negative growth in the cumulative amount of funds invested by VCs post-treatment. This finding indicates that investors offload their portfolios as their startups become more mature. The coefficient associated with the interaction between $PostAcquisition_{gt}$ and $Peer\,Acquired\,by\,Foreign\,Firm_i$ is, instead, insignificant and approximately zero. This result indicates that after a peer j is acquired by a foreign company, the growth trajectory in the cumulative amount of funds raised does not vary between treated and non-treated startups.

In columns 2 and 3 of Table 9, we further explore these findings by investigating the reaction of foreign investors. We zoom in on these investors because they have been shown to play a fundamental role in enhancing Israeli startups' value (Conti and Guzman, 2021). Column 2 reports the results for the yearly change in the natural logarithm of the cumulative amount of funds a startup obtained from US investors. These investors represent the vast majority of foreign investors funding Israeli startups and, thus, they accurately approximate the category of foreign investors.[13] As shown, the coefficient associated with $PostAcquisition_{gt}$ is positive although insignificantly different from zero. This result and the analogous effect shown in column 1 are both consistent with earlier findings showing that, relative to foreign investors, Israeli investors specialize in early stage financing (Conti and Guzman, 2021). The interaction between $PostAcquisition_{gt}$ and $PeerAcquired\,by\,Foreign\,Firm_i$ is not significantly different from zero, suggesting that the growth trajectory in the cumulative amount of funds raised from foreign investors is similar across treated and non-treated startups. This result is confirmed in both column 3 of Table 9 and Figure 4, where we restrict the set of US investors to US VCs. Taken together, these findings allow us to rule out the alternative explanation that treated startups improve their acquisition prospects because VCs invest larger amounts in them.

⟨ Insert Table 9 and Figure 4 about here ⟩

4.3.2 Demand or supply effects?

Another concern with our results is that they could be reflecting supply *and not* demand effects to the extent that an initial acquisition leads to more startups seeking acquisition opportunities. To address this concern, we examine a startup's sales price upon an acquisition.[14] The rationale is that if we are capturing supply effects only, then we should observe a decline in the sales price of startups whose technologically similar peers were acquired by a foreign company. We estimate a

[13] We make this approximation because, by inspection, identifying the exact origin of foreign investors is more complicated than identifying the origin of foreign acquirors. This is especially true when foreign investors are from outside the US.

[14] Findings reported in Appendix Table A4 show that, after the treatment, the improvement in acquisition opportunities mainly applies to treated startups in their later stages that are, thus, close to exit.

cross-sectional model limiting the sample to dyads where the observed startup was acquired:

$$Y_{ij} = \alpha Peer\,Acquired\,by\,Foreign\,Firm_i + \beta Controls_i + \gamma Controls_j + \psi_g + \eta_i + \tau_i + \varepsilon_{ij}. \qquad (2)$$

The outcome Y_{ij} is defined as the price at which startup i in dyad ij was sold (expressed in natural logarithm). Since this information is only available for 67% of the acquired startups, we estimate an alternative specification where we set the missing values to zero and generate an indicator for startups that are above the median of the sectorial distribution of sales prices. According to Nanda and Rhodes-Kropf (2013), missing values should correspond to cases in which companies were acquired at a negligible price. $Peer\,acquired\,by\,Foreign\,Firm_i$ is an indicator variable that takes value one if i's peer j is acquired by a foreign firm and zero otherwise. Because we estimate a cross-sectional model, we do not include observed or peer startup fixed effects. However, we include a fixed effect for the group g encompassing a treated startup and its controls (ψ_g), a fixed effect for i's establishment year times sector (η_i), and a fixed effect for i's exit year times sector (τ_i). We also control for the total amount of funds i and j raised by the time they were acquired, as well as for the total number of US patents the startups were granted. These variables control for relevant aspects of i's and j's quality.

The results are displayed in Table 10. Reported standard errors are clustered by treated-control groups and by i's founding year. The dependent variable in column 1 is the natural logarithm of an acquired startup's sales price. In column 2, we examine the indicator identifying startups in the top quartile of the sales price distribution. As reported in column 1, while the effect of a peer being acquired by a foreign company on an observed startup's sales price is positive, it is not significantly different from zero at conventional levels. In column 2, instead, we find that treated startups are 3.6 percentage points more likely to be acquired at a high price relative to the control group and that the effect is significant at the 5% level. Overall, these results speak against the possibility that our main findings are solely driven by supply effects. Had we captured *solely* supply effects, we would have observed a decline and not an increase in the sales price of treated startups.

⟨ Insert Table 10 about here ⟩

4.3.3 Does location matter?

Our results so far point to an increase in the demand for *Israeli* startups by foreign firms after an initial acquisition. Yet, it is possible that the herding effects are triggered by firms responding to certain technological opportunities, regardless of the location in which they are developed. To address this concern, we assess how the acquisition of an Israeli startup by a US firm affects the acquisition opportunities of other US startups developing similar technologies as the acquired Israeli company. If acquirers engage in herd behavior only to take advantage of certain technological opportunities and location does not matter, the acquisition of an Israeli company should also improve the acquisition prospects of technologically related US startups.

To implement this analysis, we estimate a difference-in-differences model similar to the one described in Section 3.1. Specifically, we examine whether the acquisition of an Israeli startup by a US firm improves the likelihood that a US startup developing a similar technology to the Israeli company is subsequently acquired. The control group is represented by US startups developing different technologies from those of the Israeli acquirees.

In practice, we first identified all the Israeli startups acquired by a US company in the Crunchbase database. We then assigned a random sample of US startups to the acquired Israeli startups, dividing the former into two groups: those sharing at least three technology keywords with the Israeli acquirees and those sharing fewer than three keywords. The first set of US startups is the one "treated" by the acquisition of the Israeli companies, given technological closeness, while the second set is the control group. Similar to the conditions we imposed in our main analyses, we excluded those US startups that had an exit prior to the acquisition date of the associated Israeli company. We further limited the US startups to those located in California, Massachusetts, or New York. As Conti and Guzman (2021) have shown, most of the Israeli startups that migrate to the US establish their headquarters in these three states. Hence, any effect stemming from the acquisition of Israeli startups should be stronger in these regions.

The results are reported in Table 11. The dependent variable is the probability that a US startup i, paired with an Israeli startup j, is acquired in year t. The *Post Israeli Acquisition*$_{gt}$ variable is a (0/1) indicator that becomes 1 after an Israeli startup is acquired, for all the US startups associated with the Israeli company. *Technologically Similar*$_i$ is an indicator identifying all the US startups sharing at least three technology keywords with the associated Israeli startup. The results in column 1 show that after an Israeli startup is acquired, US startups developing similar technologies as the initial acquiree do not improve their chances of being acquired relative to US startups that produce dissimilar technologies. This result is confirmed in column 2, where the variable *Technologically Similar*$_i$, instead, identifies all the US startups sharing at least four technology keywords with the acquired Israeli startup. Overall, these findings provide a strong indication that our herding effects are driven by acquirors reacting to opportunities in a specific ecosystem, namely the Israeli startup ecosystem. Additionally, they provide further confirmation that acquisition waves do not drive our results.

⟨ Insert Table 11 about here ⟩

4.4 Miscellaneous robustness tests

Finally, for completeness, we include in the Appendix two additional miscellaneous robustness tests. In Table A5, we add several time-varying characteristics pertaining to i, j, and the dyad ij to our main equation specification. The time-varying controls we include are: the cumulative amount of funds raised by i and j (and the corresponding interaction), the cumulative amount of US VC funds raised by i and j (including the interaction), and the cumulative number of US granted patents i and j applied for (including the interaction). Table A6 presents the results from restricting the set of foreign acquirers to US firms. The magnitudes of the estimates reported in both tables are very similar to the main effects already discussed.

5 Conclusions

This paper asks whether the initial acquisition of a startup induces imitation among potential acquirers, thereby improving exit opportunities for other technologically similar startups. In addressing this question, we fill an important gap. Although prior research has focused on the characteristics of target startups and their investors, and on business cycles, as drivers of startup acquisitions, we contribute by providing evidence of herding among prospective acquirers. We additionally show that herd behavior is at least in part motivated by acquirers coping with their limited information on potential targets.

We employ international acquisitions as an empirical setting. Using rich data on the population of Israeli startups that obtained VC financing between 2002 and 2019, we evaluate how the initial acquisition of an Israeli startup by a foreign firm stimulates the demand for Israeli startups by other foreign firms, comparing their reaction to that of domestic firms. Having applied machine learning methods to construct dyads of technologically similar companies and estimated difference-in-differences and instrumental variable models, we find that the acquisition of a startup by a foreign company increases the chances that its peer is also acquired by a foreign company by 61%. Consistent with informational herding, whereby foreign acquirers imitate their predecessors to deal with market uncertainties, we find that this effect is double that on the likelihood that a startup is acquired by a domestic firm.

We provide several additional results that elucidate the mechanisms behind our main results. First, the effect on the likelihood that a startup is acquired by a foreign firm intensifies when we adopt more stringent criteria for defining dyads of technologically similar startups. Second, the effect becomes null when the initial acquisition is undertaken by an Israeli firm. Third, the effect becomes stronger when an initial acquisition is enacted by a prominent foreign firm. Fourth, the less informed foreign acquirers -namely, non-US acquirers and foreign acquirers without an R&D center in Israel- respond more strongly to prominent acquisitions of Israeli startups than to non-prominent acquisitions, relative to the better informed foreign acquirers.

Our fine-grained data allow us to rule out several alternative interpretations. For instance, we show that our findings are not driven by intensified VCs' activities that would enhance their portfolio startups' value, making these companies more attractive to foreign acquirers. Indeed, we find that neither domestic nor foreign investors invest larger amounts in their companies after technologically similar peers have been acquired. Moreover, we show that startups whose technologically similar peers were acquired by a foreign company sell at a higher price than their controls. This evidence speaks against the possibility that our results capture solely an increase in the supply of startups seeking acquisition opportunities. Additionally, we show that our results hold after replacing subsector by year fixed effects with technology keyword by year fixed effects. As there are approximately 700 technology keywords describing our startup technologies, this last analysis mitigates the concern that our results are driven by acquisition waves following specific technology shocks rather than by mimicry.

Finally, we show that after an Israeli startup is acquired, US startups developing similar technologies as the acquired startup do not improve their acquisition chances relative to US startups that produce dissimilar technologies. This result provides a strong indication that our herding effects are driven by firms reacting to technological opportunities in a specific ecosystem rather than responding to opportunities regardless of the location in which they are developed.

These findings have clear implications for policy makers building or expanding their startup ecosystems. One of the major obstacles policy makers around the world encounter is the limited availability of potential acquirers that could offer exit opportunities to domestic startups. Our results show that an initial acquisition can generate a cascade effect, inducing imitation by other firms and improving the acquisition prospects of startups embedded in a given ecosystem. This insight raises a number of additional questions, and opens avenues for future research. Two extensions are immediately clear. First, while herding behavior among acquirers appears to benefit a given ecosystem, it may be detrimental to the acquirers as information could stop accumulating after a while. As a topic for future research, it would be interesting to assess the overall welfare implications of herding in the context of startup acquisitions. Second, future empirical investigation could extend our analyses to the behavior of intermediate investors. Our sample is limited to startups that raised at least one round of financing. Thus, we cannot assess whether an initial acquisition stimulates investors, especially foreign ones, to invest in nascent startups that are technologically related to the acquiree. Future research could investigate these VC reactions.

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Tables & Figures

Herding in the Market for Startup Acquisitions

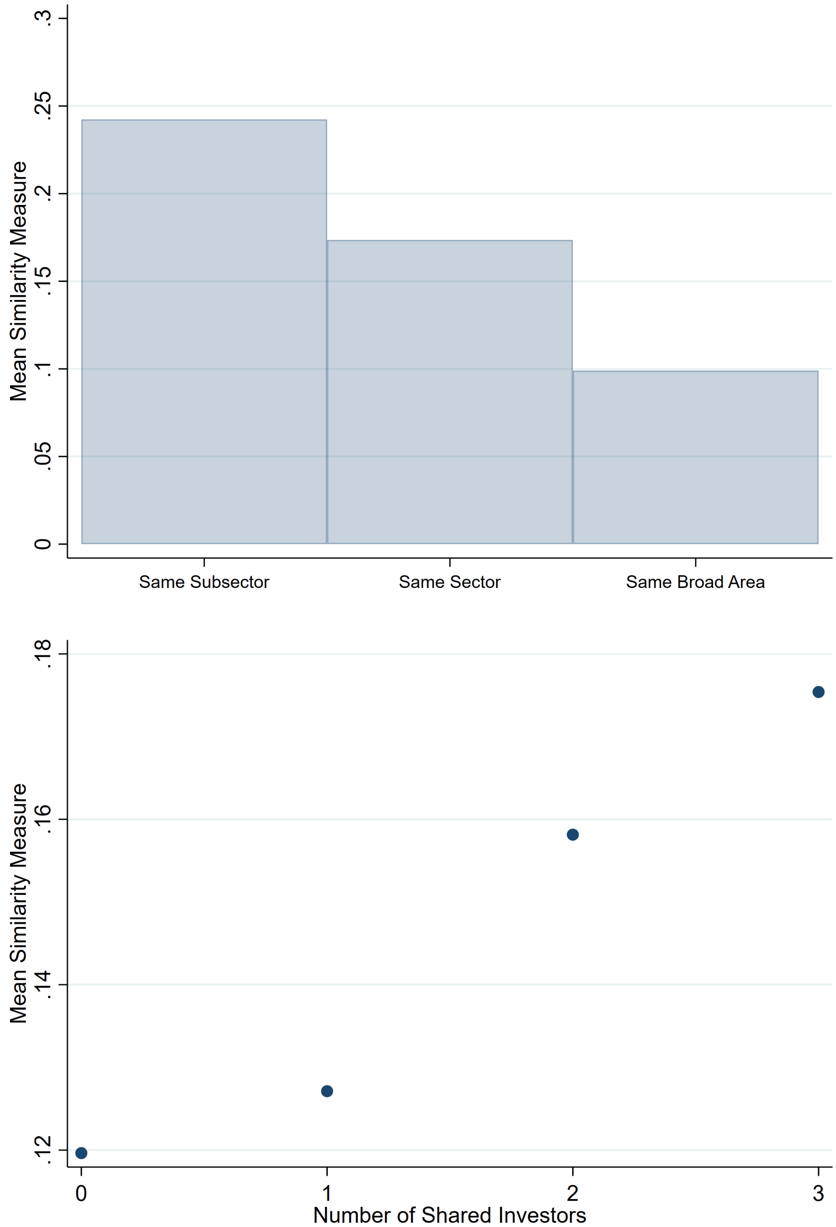

Figure 1: Assessing the technology similarity between dyadic peers

Notes: The figure at the top of the page shows how the similarity between two startups in a dyad varies according to whether the startups belong to the same subsector (a list of subsectors is provided in Table A1 of the Appendix), sector (cleantech, communications, IT & enterprise software, Internet, life sciences, semiconductors, and miscellaneous technologies), or broad area (cleantech, life sciences, Internet, and the remainder). We define the similarity between two startups i and j in a dyad as: $\frac{NSharedTags_{ij}}{min(NTags_i, NTags_j)}$ that is, the ratio of the number of technology keywords that i and j share to the minimum number of keywords between i and j. This measure was calculated for all possible dyadic combinations of the 5,725 startups belonging to our sample. The figure at the bottom plots the mean similarity measure over the number of investors that the startups in a dyad have in common.

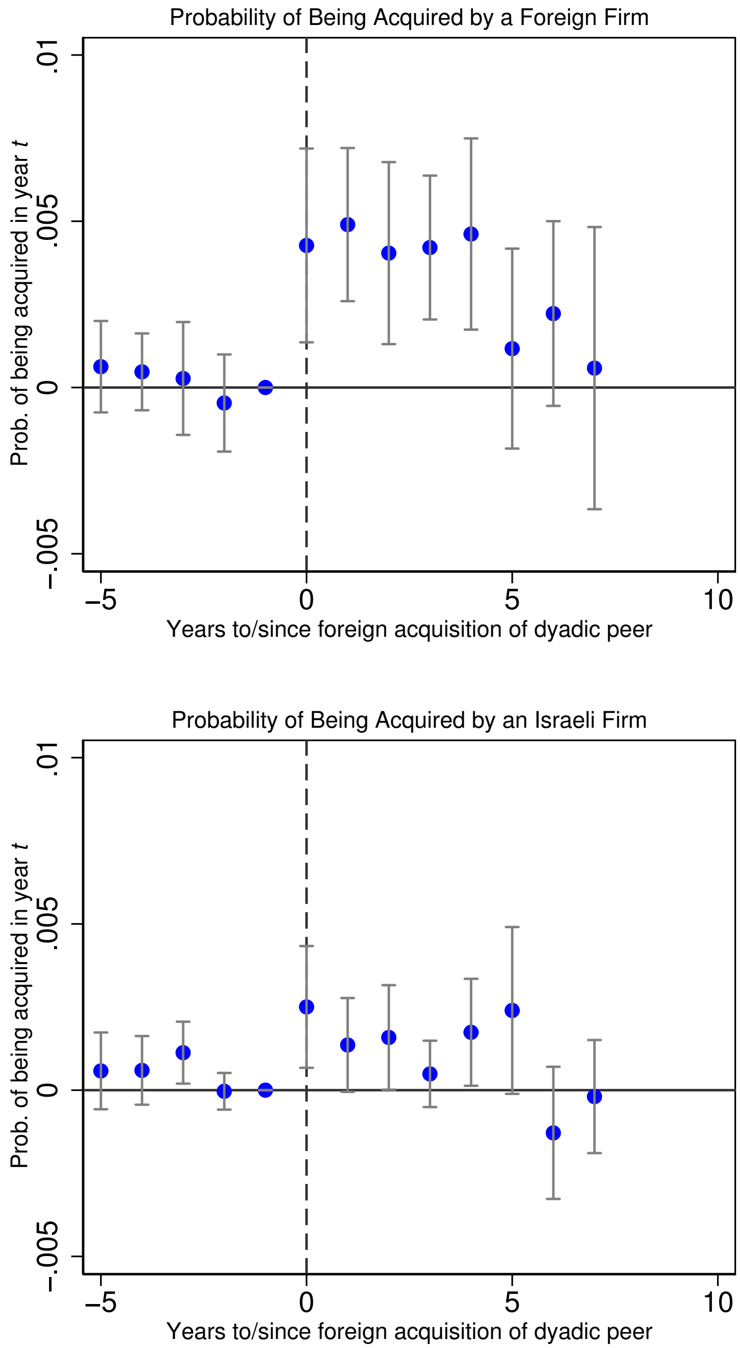

Figure 2: The effect of an acquisition by a foreign firm on the Israeli market for acquisitions

Notes: This figure shows how the probability that a startup is acquired by a foreign firm (top) and the probability that a startup is acquired by an Israeli firm (bottom) in a given year change after a startup's technologically similar peer is acquired by a foreign firm. To generate these graphs, we modified Eq. (1) in the main text by substituting the $PostAcquisition_{gt}$ indicator with binary variables for each of the pre- and post-treatment years. We interacted these year indicators with *Peer Acq. by Foreign Firm*$_i$, which equals one if the peer j of a startup i is acquired by a foreign firm and zero otherwise. In the graphs, we report the coefficients for these interactions. The vertical bars represent 95% confidence intervals. The coefficient for the year immediately before the acquisition event is set to 0 and displayed without a confidence interval because it is our baseline year.

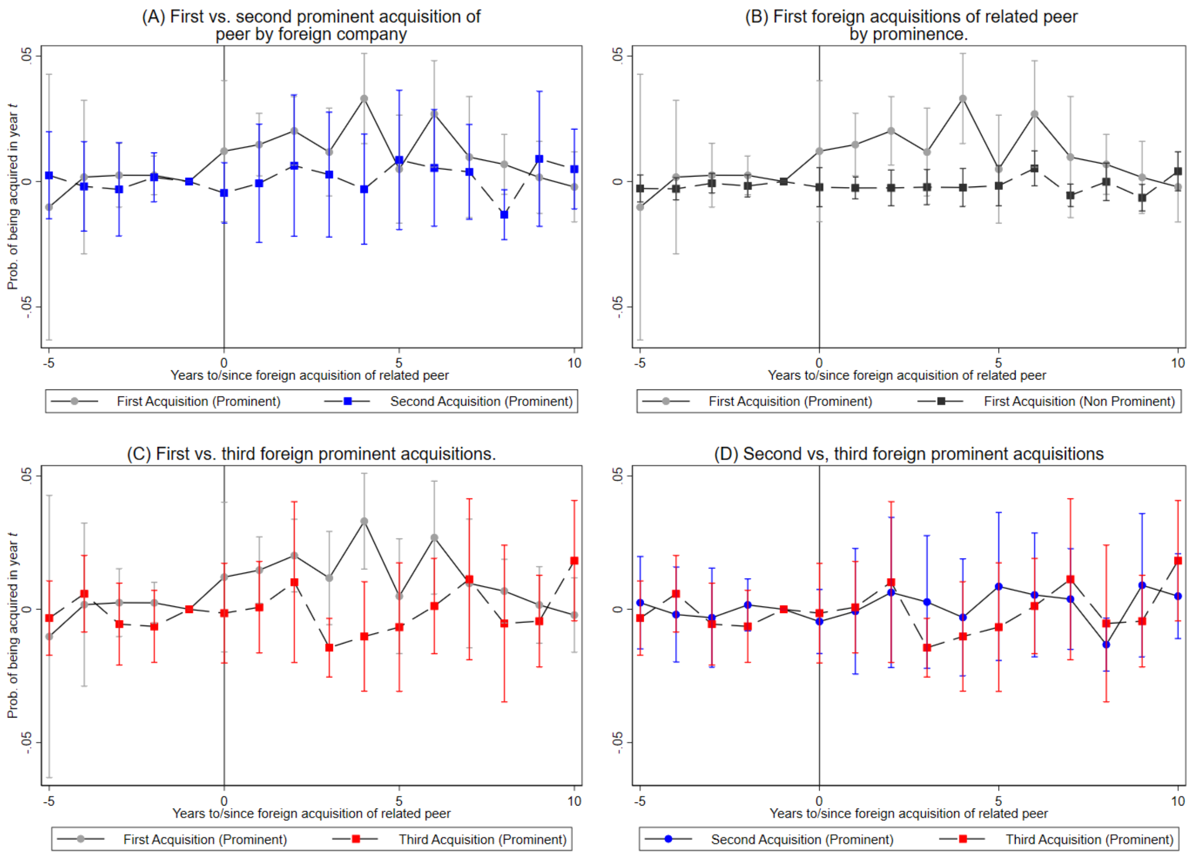

Figure 3: Acquisition dynamics

Notes: This figure illustrates how an observed startup's exit outcome responds to the earlier versus later foreign acquisitions of technologically similar peers, and further investigates whether any reaction depends on the prominence of a given acquisition. To perform this analysis, we condition on those instances in which the peers *j*s of a given startup *i* were acquired by a foreign company and rank these acquisition events from the earliest to the more recent. We then examine how *i*'s chances of being acquired by a foreign company vary pre- and post-treatment, comparing earlier to more recent treatments and, moreover, contrasting prominent with less prominent treatments. Panel A (top left) plots the year coefficients pre and post the prominent acquisition of *i*'s peer *j* by a foreign company, having distinguished between the earliest (i.e., first) and the second acquisition. As shown, the earliest acquisition produces stronger effects than the more recent one. Panel B (top right) zooms in on the earliest foreign acquisitions, contrasting prominent with non-prominent acquisitions. The treatment effects of an earliest acquisition are greater than zero only if such an acquisition is prominent. Panel C (bottom left) contrasts the earliest prominent acquisition of *i*'s peer *j* by a foreign company with the third of such events. The displayed pattern is similar to the one depicted in Panel A. Finally, Panel D (bottom right) compares the second to the third prominent acquisition of *i*'s peers. Here, we continue to find that earlier prominent acquisitions of *i*'s peers by foreign acquirers generate stronger effects than the more recent treatments, although the difference in effects is less pronounced.

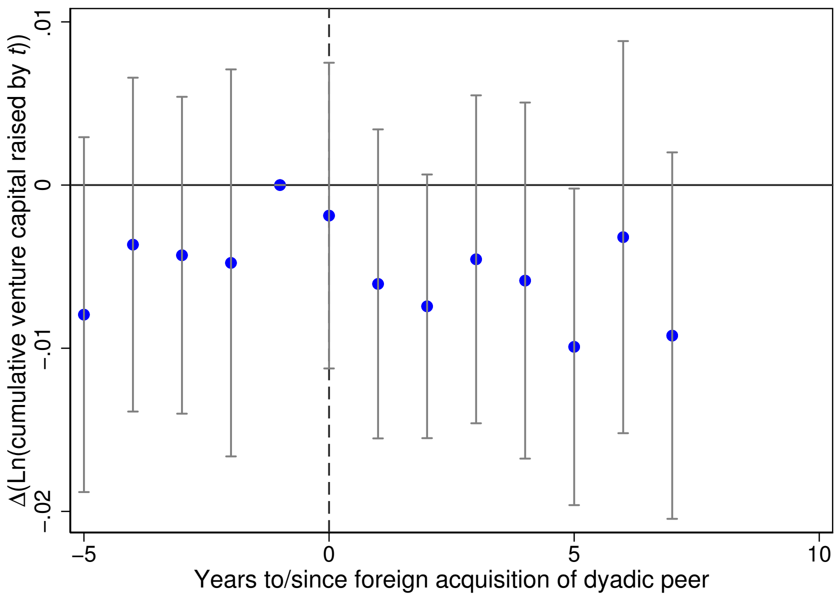

Figure 4: The effect of an acquisition by a foreign firm on foreign VC investment

Notes: This figure illustrates how the cumulative amount of funds raised from US VCs changes after a startup's technologically similar peer is acquired by a foreign firm. US investors represent the vast majority of foreign investors funding Israeli startups and, thus, they accurately approximate the category of foreign investors. The analyzed outcome in this graph is startup i's yearly change in the cumulative amount of US VC funds received. To generate this graph, we modified Eq. (1) in the main text by substituting the $PostAcquisition_{gt}$ indicator with binary variables for each of the pre- and post-treatment years. We interacted these year indicators with *Peer Acq. by Foreign Firm*$_i$, which equals one if the peer j of a startup i is acquired by a foreign firm and zero otherwise. In the graph, we report the coefficients for these interactions. The vertical bars represent 95% confidence intervals. The coefficient for the year immediately before the acquisition event is set to 0 and displayed without a confidence interval because it is our baseline year.

Table 1: Summary statistics for the startups in our sample

	mean	sd	min	p50	max
Startup sectors					
Cleantech	0.09	0.28	0	0	1
Communications	0.17	0.37	0	0	1
IT & Enterprise Software	0.23	0.42	0	0	1
Internet	0.21	0.41	0	0	1
Life Sciences	0.23	0.42	0	0	1
Miscellaneous Technologies	0.06	0.24	0	0	1
Semiconductor	0.03	0.16	0	0	1
Startup-level financing statistics					
Raised funds from VCs	0.38	0.48	0	0	1
Raised funds from US VCs	0.16	0.37	0	0	1
Cum. amount of funds ($ mill.)	8.06	29.88	0	0.66	850
Cum. amount of US funds ($ mill.)	5.15	25.1	0	0	850
Cum. amount of US VC ($ mill.)	3.55	19.78	0	0	611.6
N rounds raised	1.72	1.19	1	1	10
Cum. number of US patents	1.23	5.49	0	0	191
Startup-level exit statistics					
Had an Exit (IPO/Acquisition)	0.14	0.35	0	0	1
Had an IPO	0.02	0.14	0	0	1
Was Acquired	0.12	0.33	0	0	1
Was Acquired by foreign company	0.08	0.27	0	0	1
Was Acquired by US company	0.06	0.23	0	0	1
Was Acquired by Israeli company	0.04	0.2	0	0	1
Sales price ($ mill.)	111.08	691.77	0.13	25	15300
Observations			5725		

Notes: Descriptive statistics for the startups in our sample. The startups raised a financing round between 2002 and 2019 and were founded between 1998 and 2018. The sales price statistics were computed for the set of companies that were acquired and for which we have information on sales price. The *Raised funds from VCs* variable is a (0/1) indicator identifying startups that raised funds from venture capitalists (VCs). The *Raised funds from US VCs* variable is a (0/1) indicator identifying startups that raised funds from US VCs. *Cum. amount of funds* denotes the cumulative amount of funds a startup raised from establishment until 2019. To compute the cumulative amount of funds a startup raised from US investors (*Cum. amount of US funds*), we only summed those amounts raised during rounds in which at least one US investor participated. Similarly, the cumulative amount of funds a startup raised from US VCs (*Cum. amount of US VC funds*) was obtained by summing those amounts raised during rounds in which at least one US VC participated.

Table 2a. Summary statistics at the startup-dyad level, by treatment

	(1) Treatment=1		(2) Treatment=0		(3)
	mean	s.d.	mean	s.d.	diff.
Had an exit (IPO/Acquisition)	0.1411	0.3481	0.0903	0.2865	0.0508***
Had an IPO	0.0054	0.0730	0.0097	0.0979	-0.0043***
Was acquired	0.1339	0.3406	0.0792	0.2701	0.0547***
Was acquired by foreign company	0.0885	0.2840	0.0485	0.2149	0.0399***
Was acquired by US company	0.0635	0.2438	0.0343	0.1821	0.0292***
Was acquired by Israeli company	0.0455	0.2083	0.0307	0.1725	0.0148***
Sales price ($ mill.)	96.9456	422.3059	72.5511	146.3547	24.3945***
Cum. amount of funds ($ mill.)	10.8630	28.7546	8.7623	29.4244	2.1007***
Cum. amount of US funds ($ mill.)	5.7809	21.7008	4.6269	24.0389	1.1540***
Cum. amount of US VC funds ($ mill.)	3.8354	17.9611	2.9699	18.4428	0.8655***
Cum. number US patents	1.4963	5.8626	1.4587	5.5333	0.0375
Observations	16038		117160		

Notes: *Treatment* is equal to one if an observed startup is matched with a peer that is acquired by a foreign company and zero otherwise. In building the sample, we generate g groups of treated and control startups such that each treated startup belonging to dyad ij is randomly assigned ten control startups whose peers are not acquired by a foreign firm. We impose that the control startups are established during the same year as the treated startups, but in a different sector. We remove from the sample those dyads in which the observed company was established at least five years prior to its peer. Furthermore, we exclude from the sample those instances where the treatment occurs after a given startup i assigned to dyad ij and group g experiences an exit event (either an acquisition or an IPO). Additionally, we exclude startups that share fewer than three technology keywords with their peers. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 2b. Summary statistics at the startup-dyad-year level, by treatment

	(1) Treatment=1		(2) Treatment=0		(3)
	mean	s.d.	mean	s.d.	diff.
Had an exit$_t$ (IPO/Acquisition)	0.0219	0.1463	0.0097	0.0981	0.0122***
Had an IPO$_t$	0.0008	0.0288	0.0010	0.0323	-0.0002*
Was acquired$_t$	0.0208	0.1426	0.0085	0.0920	0.0122***
Was acquired by foreign company$_t$	0.0137	0.1163	0.0052	0.0721	0.0085***
Was acquired by US company$_t$	0.0098	0.0987	0.0037	0.0607	0.0061***
Was acquired by Israeli company$_t$	0.0071	0.0837	0.0033	0.0574	0.0037***
Cum. amount of funds$_t$ ($ mill.)	9.3241	23.1524	6.1036	22.2645	3.2205***
Cum. amount of US funds$_t$ ($ mill.)	4.4347	17.4300	2.7611	18.5412	1.6736***
Cum. amount of US VC funds$_t$ ($ mill.)	2.8999	14.7057	1.7466	13.7265	1.1533***
Cum. number US patents$_t$	1.4188	5.0785	1.1713	4.3248	0.2475***
Observations	103391		1087876		

Notes: *Treatment* takes the value one after the peer of a treated startup is acquired by a foreign firm and zero otherwise. For details on the sample construction refer to the notes in Table 2a.

Table 3. Startup liquidity events after a peer is acquired by a foreign company

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by Foreign Firm	(4) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0193***	0.0171***	0.0106***	0.00646***
	(0.000791)	(0.000746)	(0.000721)	(0.000666)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00434***	0.00471***	0.00365***	0.00106***
	(0.000574)	(0.000527)	(0.000504)	(0.000313)
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y	Y	Y
Treated-Control Startup Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
Dyads	133198	133198	133198	133198
Groups of Treated-Control Startups	48237	48237	48237	48237
R2	0.128	0.131	0.124	0.148
Mean Outcome Variable	0.01078	0.00959	0.00596	0.00363

Notes: This table reports the results from estimating linear probability models for the likelihood that a startup i belonging to dyad ij is: i) either acquired or goes public via an IPO in year t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm$_i$* is an indicator that equals one if the peer j of a startup i is acquired by a foreign firm and zero otherwise. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a foreign firm. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 4. Startup acquisition events after a peer is acquired by a foreign company: IV Models

	(1) Acquired by Foreign Firm	(2) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.00929***	0.00691***
	(0.00142)	(0.000910)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00400***	0.000963**
	(0.000613)	(0.000368)
Dyad FEs	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y
Treated-Control Startup Groups FEs	Y	Y
Observations	1055861	1055861
Dyads	130990	130990
Groups of Treated-Control Startups	47432	47432
Mean Outcome Variable	0.00652	0.00396
Cragg-Donald Wald F stat.	23.74	

Notes: This table reports the results from estimating 2SLS models for the likelihood that a startup is: i) acquired by a foreign company in year t (column 1); and ii) acquired by an Israeli company (column 2). These models address the possible concern that we might have omitted some time-varying factors confounding the relationship between the treatment and the likelihood that an observed startup i from dyad ij experiences a given acquisition event. We follow Freyaldenhoven *et al.* (2019) and estimate a 2SLS model wherein we exploit a time-varying covariate that is plausibly correlated with possible time-varying confounds. Specifically, we control for the cumulative likelihood that a startup will have applied for a patent with the USPTO by t and instrument this variable with the first lead of *Peer Acq. by Foreign Firm*$_i$ $\times$ *Post Acquisition*$_{gt}$. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 5. Strengthening the criteria for selecting technologically similar dyads

	ij shares a relevant technology keyword					
	(1)	(2)	(3)	(4)	(5)	(6)
	Acquisition/IPO	Acquired	Acquired by Foreign Firm		Acquired by Israeli Firm	
Post Acquisition$_{gt}$	0.0202***	0.0170***	0.0106***	0.00915***	0.00648***	0.00553***
	(0.00109)	(0.000858)	(0.000969)	(0.00100)	(0.000863)	(0.000837)
Peer Acq. by Foreign Firm$_i$ × Post Acquisition$_{gt}$	0.00551***	0.00648***	0.00477***	0.00478***	0.00171**	0.00139**
	(0.00109)	(0.00115)	(0.00105)	(0.000776)	(0.000744)	(0.000540)
Dyad FEs	Y	Y	Y	Y	Y	Y
Year FEs × Obs. Startup Subsector FEs	Y	Y	Y		Y	
Year FEs × Peer Startup Subsector FEs	Y	Y	Y		Y	
Year FEs × Obs. Startup Keyword FEs				Y		Y
Year FEs × Peer Startup Keyword FEs				Y		Y
Treated-Control Startup Group FEs	Y	Y	Y	Y	Y	Y
Observations	453070	453070	453070	4453070	453070	453070
Dyads	50017	50017	50017	50017	50017	50017
Groups of Treated-Control Startups	32490	32490	32490	32490	32490	32490
R2	0.128	0.132	0.127	0.244	0.145	0.269
Mean Outcome Variable	0.01065	0.00908	0.00565	0.00565	0.00342	0.00342

Notes: This table reports the results from estimating linear probability models for the likelihood that a startup is: i) either acquired or goes public via an IPO in year t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (columns 3 and 4); and iv) acquired by an Israeli company (columns 4 and 6). Refer to the notes in Table 3. The results in this table are obtained from imposing the criteria that the dyad ij share at least three technology keywords *and* that at least one of these keywords is among the three most relevant for describing i's and j's technology according to our machine learning algorithm (Please refer to Appendix A.1 for details regarding the algorithm). In columns 4 and 6, we replace the subsector (times year) fixed effects with fixed effects for the most relevant technology keyword -according to our machine learning algorithm- describing i's and j's technology. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 6. Likelihood that a startup is acquired by a foreign company after its peer is acquired by an Israeli company

	(1) Acquired by Foreign Firm
Post Acquisition$_{gt}$	0.00529***
	(0.000546)
Peer Acq. by Israeli Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.000748
	(0.000812)
Dyad FEs	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y
Treated-Control Startup Group FEs	Y
Observations	824186
Dyads	90442
Groups of Treated-Control Startups	29341
R2	0.124
Mean Outcome Variable	0.00708

Notes: This table reports the results from estimating a linear probability model for the likelihood that a startup i belonging to dyad ij is acquired by a foreign company in year t. *Peer Acq. by Israeli Firm$_i$* is an indicator that equals one if the peer j of a startup i is acquired by an Israeli firm and zero otherwise. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by an Israeli firm. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 7: Distinguishing between prominent and less prominent foreign acquisitions of peers

	Acquired by Foreign Firm	
	Prominent Acq. I (1)	Prominent Acq. II (2)
Post Prominent Acq.$_{gt}$	0.00650*** (0.000720)	0.0106*** (0.000928)
Peer Acq. by Prominent Foreign Firm$_i$ $\times$ Post Prominent Acq.$_{gt}$	0.00501*** (0.000765)	0.00814*** (0.00148)
Post Non-Prominent Acq.$_{gt}$	0.00665*** (0.000561)	0.0106*** (0.000708)
Peer Acq. by Non-Prominent Foreign Firm$_i$ $\times$ Post Non-Prominent Acq.$_{gt}$	0.00331*** (0.000539)	0.00335*** (0.000479)
Dyad FEs	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y
Treated-Control Startup Group FEs	Y	Y
Observations	1191267	1191267
R2	0.123	0.124

Notes: We assess how the effect of a peer being acquired by a foreign firm varies depending on whether the acquisition is prominent or not. In column 1, we identify as prominent acquisitions those enacted by prominent acquirers. In column 2, we refine the notion of prominent acquisitions and retain only those that received widespread media attention and whose sales price is above the sector median for a given year. To measure media attention, we collected from LexisNexis news reports concerning the acquisition of a startup that were published between six months before and six months after the acquisition event. Building on these data, a prominent acquisition is considered to have received widespread media attention if the number of news reports mentioning it is above the sector median. We implement the analysis by substituting in Eq. (1) the *Peer Acq. by Foreign Firm*$_i$ variable with two indicators, respectively identifying prominent and less prominent acquisitions of peers js. Additionally, the *Post Acquisition*$_{gt}$ indicators identify the post-treatment period, having distinguished between prominent and less prominent acquisitions. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 8. Exploring heterogeneity in the reaction to prominent and less prominent acquisitions of peers

	(1) Acquired by US Firm	(2) Acquired by EU or Asian Firm	(3) Acquired by Foreign Firm with R&D Center in Israel	(4) Acquired by Foreign Firm with no R&D Center in Israel
Post Prominent Acq.$_{gt}$	0.00826***	0.00235***	0.00234***	0.00826***
	(0.00106)	(0.000405)	(0.000526)	(0.000827)
Peer Acq. by Prominent Foreign Firm$_i$ × Post Prominent Acq.$_{gt}$	0.00570***	0.00244**	0.00177*	0.00638***
	(0.00107)	(0.00101)	(0.000849)	(0.000961)
Post Non-Prominent Acq.$_{gt}$	0.00792***	0.00270***	0.00221***	0.00841***
	(0.000849)	(0.000350)	(0.000424)	(0.000625)
Peer Acq. by Non-Prominent Foreign Firm$_i$ × Post Non-Prominent Acq.$_{gt}$	0.00274***	0.000610**	0.000979***	0.00237***
	(0.000387)	(0.000243)	(0.000209)	(0.000447)
Dyad FEs	Y	Y	Y	Y
Year FEs × Obs. Startup Subsector FEs	Y	Y	Y	Y
Year FEs × Peer Startup Subsector FEs	Y	Y	Y	Y
Treated-Control Startup Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
R2	0.123	0.125	0.128	0.125

Notes: This table explores heterogeneity in the reaction to prominent and less prominent acquisitions of startup peers. The outcomes examined are the likelihoods that observed startups are acquired in t by: i) US firms (column 1); ii) European or Asian firms (column 2); iii) foreign firms with R&D centers in Israel (column 3); and iv) foreign firms with no R&D centers in Israel (column 4). We identify as prominent acquisitions those enacted by prominent acquirers and such they received widespread media attention and the sales price is above the sector median. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 9: Amount of funds raised

	(1) Δln(Cum. Amount)	(2) Δln(Cum. US Amount)	(3) Δln(Cum. US VC Amount)
Post Acquisition$_{gt}$	-0.0121***	0.00223	0.000929
	(0.00318)	(0.00171)	(0.00123)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	-0.000587	-0.00189	-0.00234
	(0.00222)	(0.00178)	(0.00191)
Dyad FEs	Y	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y	Y
Treated-Control Startup Group FEs	Y	Y	Y
Observations	1191267	1191267	1191267
Dyads	133198	133198	133198
Groups of Treated-Control Startups	48237	48237	48237
R2	0.266	0.218	0.225

Notes: This table reports the results from estimating a linear regression for the yearly change in the log of: the cumulative amount of funds raised (column 1), the cumulative amount of funds raised from US investors (column 2), and the cumulative amount of funds raised from US VCs (column 3). *Peer Acq. by Foreign Firm$_i$* is an indicator that equals one if the peer j of a startup i is acquired by a foreign firm. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a foreign firm. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 10: Startup sales price

	(1) Sales Price (log)	(2) Sales Price (indicator)
Peer Acq. by Foreign Firm$_i$	0.127	0.0363**
	(0.116)	(0.0169)
Cum. amount of funds - obs. startup (log)	0.448***	0.150***
	(0.120)	(0.0337)
Cum. amount of patents - obs. startup (log)	0.265**	0.0950**
	(0.104)	(0.0336)
Cum. amount of funds - peer startup (log)	0.0211	0.00438
	(0.0217)	(0.00779)
Cum. amount of patents - peer startup (log)	0.00721	0.0231
	(0.0510)	(0.0187)
Obs. Startup Exit Year FEs $\times$ Sector FEs	Y	Y
Obs. Startup Founding Year $\times$ Sector FEs	Y	Y
Treated-Control Startup Group FEs	Y	Y
Groups of Treated-Control Startups	696	1380
Observations	1438	2908
R2	0.863	0.738

Notes: This table reports the results from estimating Eq. (2). We perform a cross-section analysis to assess how an observed startup's sales price varies depending on whether its peer was acquired by a foreign company. We limit the analysis to those dyads *ij* wherein the observed company *i* was acquired. The dependent variable in column 1 is the natural logarithm of an acquired startup's sales price. We exclude from the analysis those dyads in which there is missing information on *i*'s sales price. The dependent variable in column 2 is an indicator identifying startups that are above the median of the sectorial distribution of sales prices. The indicator is set to zero for those acquired startups with missing sales price information. Standard errors (in parentheses) are multi-way clustered by groups of treated and control startups and by *i*'s establishment year. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 11: US Startup acquisition events after an Israeli peer is acquired by a US company

	(1) Acquisition	(2) Acquisition
Post Israeli Acquisition$_{gt}$	0.03873***	0.03950***
	(0.00178)	(0.00187)
Tech. Similar$_i$ $\times$ Post Israeli Acq.$_{gt}$	0.00224	0.0006
	(0.00136)	(0.00394)
Dyad FEs	Y	Y
Year FEs $\times$ US Startup Tech. FEs	Y	Y
Year FEs $\times$ Israeli Startup Tech. FEs	Y	Y
Dyads	26786	26786
Groups of Treated-Control Startups	232	232

Notes: This table reports the results from estimating a linear probability model for the likelihood that a US startup i belonging to dyad ij is acquired in year t. To construct the dyads, we considered all Israeli startups that were acquired by a US company. We identified their profile in the Crunchbase database. We successively generated dyads of Israeli-US startups. The US startups were matched with the Israeli ones as follows. We randomly selected a sample of US startups sharing at least three technology keywords (assigned by Crunchbase) with the Israeli companies and a sample of US startups sharing less than three keywords. The first set of US startups is the one "treated" by the acquisition of the Israeli company, while the second set is the control group. We further imposed that the US companies should be founded within five years from the Israeli startups' inception and should be in California, Massachusetts, or New York. Finally, we excluded those US companies that had an exit prior to the acquisition date of the associated Israeli company. In the model, *Post Israeli Acquisition*$_{gt}$ is a (0/1) indicator that becomes 1 after an Israeli startup is acquired, for all the US startups associated with the Israeli company. *Tech. Similar*$_i$ is an indicator identifying all the US startups sharing at least three technology keywords with the associated Israeli startup. In column 3, *Tech. Similar*$_i$, instead, identifies all the US startups sharing at least four technology keywords. We include fixed effects for the *ij* dyad and for the most relevant technology keywords -describing i and j- times year. Standard errors are multi-way clustered by year, acquired Israeli startup, and associated US startup. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Appendix

A.1 Details on the construction of startup dyads

To assess herding effects, we implemented a machine learning algorithm that helped us construct dyads of companies developing similar technologies. In what follows, we describe the procedure adopted.

To start, we considered the keywords that IVC uses to describe a startup's technology. As an example, the technology that the company Waze develops is described by the following keywords: Mobile GPS, Social Mobile Application, Location Based Services, Social Commuting, and Geogaming. The total number of technology keywords is 731. For a subsample of approximately 15% of companies, we have IVC information gathered at three distinct points in time: 2009, 2014, and 2020. By inspection, the keywords that the startups are originally assigned remain unchanged over time.

The IVC keywords are available for approximately 74% of the sample companies. To keep the remaining 26% of the companies, we implemented a machine learning algorithm. This algorithm assigns each company a set of technology keywords. Note that those companies whose technology was originally described by a set of keywords are re-assigned a new set.

The algorithm exploits the richness of the IVC data, which includes generic company descriptions, as well as in-depth descriptions of the companies' technologies and their targeted markets. Importantly, these descriptions -along with the technology keywords- tend to remain unchanged over time. Thus, we can make the assumption that they reflect the technologies and products that the companies had started developing at the time they were founded.

The algorithm proceeds in two steps. The first is a vectorization step that uses the Term Frequency–Inverse Document Frequency (TF-IDF) procedure. The second is a classification step done using the K Nearest Neighbors (KNN) algorithm.[15] The first step was performed using the Scikit-Learn Python package, more specifically a CountVectorizer and a TfidfTransformer.

[15] For details, refer to Jo (2016).

We concatenated all the descriptions pertaining to a given company generating one document per company and successively eliminated commonly used words (stopwords) such as "and" or "the". From the processed documents, we created a unique corpus of words. This corpus was fed into a CountVectorizer instance (with default parameters) which generated a matrix of word counts for each document. This matrix was successively fed into TfidfTransformer to create a matrix of adjusted word scores using the TF-IDF method. Dimensionality reduction was not used as the results were noticeably improved by omitting this step.

The second step is a multi-label classification procedure that uses the KNN algorithm. The implementation used is the Scikit-Learn's KNN Classifier with default parameters (k = 5, Euclidean distance metric, uniform weights). The dataset was separated into labeled (i.e., instances where keywords were originally assigned) and unlabeled (i.e., instances without keywords) data. The labeled data was used to train the classifier as follows: the features of the classifier were the raw TF-IDF vectors, and the labels were the sum of the one-hot encoded keywords. The set of keywords used to label each company in the dataset corresponds to the union of all existing keywords in the original dataset.

Building on the two steps just described, each company was assigned a set of probabilities summarizing the relevance of a given technology keyword from the set above for describing the company's technology. The probabilities were thresholded to create the final classification. The threshold was dynamically lowered for each company until that company was described by at least three keywords. As a result of this procedure, the average (median) startup in our sample has 7.76 (6) keywords describing its technology.

As an example of the output generated, the company Waze was re-assigned the following keywords: Automotive, Transportation, GPS, Big Data, Smart City, and Internet of Things. To give another example, the company Accurate Watering, which was originally not described by any keyword, was assigned the following keywords: Smart Irrigation, AgriTech, Watertech, Internet of Things. This is based on the IVC company description "Accurate Watering is developing an adjustable pop-up sprinkler for the precise irrigation of non regular areas. Smart Irrigation System," technology description "Smart Irrigation System," and targeted market description "Industrial Companies, Agriculture & Irrigation Industry, Landscape & Turf Irrigation Market."

A.2 Additional Figures & Tables

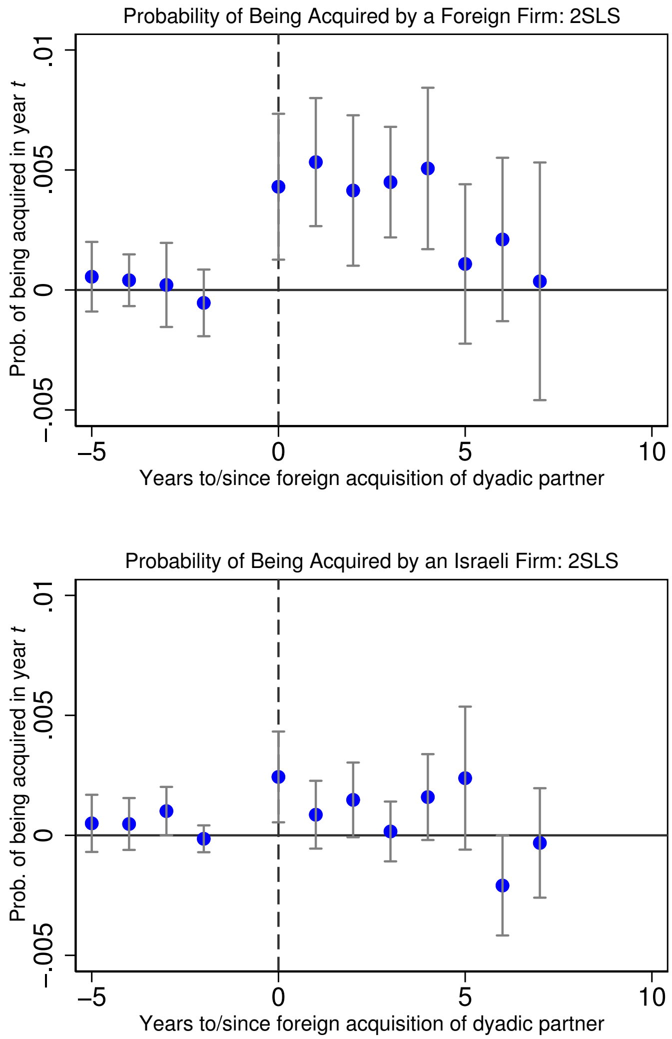

Figure A1: Panel event study following Freyaldenhoven et al. (2019)

Notes: Time-varying unobserved factors potentially cause endogeneity, manifested as a pre-trend in the acquisition outcomes. A startup's patent output is likely to be affected by the confounds, but, as we mention in the main text, unlikely to be triggered by the acquisition of a startup's peer. Applying the approach by Freyaldenhoven et al. (2019), we use this covariate to learn the dynamics of the confounds and adjust for them in a 2SLS model. The top figure reports the coefficients of the 2SLS model for the likelihood that startup i is acquired by a foreign company in year t using the first lead of the interaction between $PeerAcquired\,by\,Foreign\,Firm_i$ and $PostAcquisition_{gt}$ to instrument for the cumulative likelihood that a startup i applied for a US granted patent. We include the same fixed effects as those listed in Eq. (1). The bottom figure reports the coefficients of the same 2SLS model as in the top figure, but for the likelihood that i is acquired by an Israeli company in t.

Table A1: List of subsectors (as defined by IVC)

Cleantech:	**Internet**:
Agrotech	Content Delivery Platforms
Energy	Content Management
Environment	E-Learning
Materials	Internet Applications
Water Technologies	Internet Infrastructure
Communications:	Online Advertising
Broadband Access	Online Entertainment
Broadcast	Search Engines
Enterprise Networking	Social Networks
Home Networking	E-commerce
Mobile Applications	**Life Sciences**:
Mobile Infrastructure	Biotechnology
NGN & Convergence	Digital Health
Optical Networking	Medical Devices
Security	Pharmaceuticals
Telecom Applications	**Semiconductors**:
VoIP & IP Telephony	Fabrication & Testing
Wireless Applications	Manufacturing Equipment & EDA
Wireless Infrastructure	Memory & Storage
IT & Enterprise Software:	Miscellaneous Semiconductors
Business Analytics	Network Processors
Content Delivery Platforms	Processors & RFID
Design & Development Tools	Security Semiconductors
Enterprise Applications	Video, Image & Audio
Enterprise Infrastructure	Wireless Communication
Miscellaneous Software	Wireline & Home Networking
Security	**Miscellaneous Technologies**:
Hardware	Defense
	Industrial Technologies
	Miscellaneous
	Nanotechnology

Table A2. Startup liquidity events after a peer is acquired by a foreign company: Distinguishing between larger and smaller foreign acquirers

	(1) Acquired by Large Foreign Firm	(2) Acquired by Smaller Foreign Firm
Post Acquisition$_{gt}$	0.00401***	0.00661***
	(0.000423)	(0.000508)
Peer Acq. by Foreign Firm$_i$ × Post Acquisition$_{gt}$	0.00144***	0.00221***
	(0.000321)	(0.000451)
Dyad FEs	Y	Y
Year FEs × Obs. Startup Subsector FEs	Y	Y
Year FEs × Peer Startup Subsector FEs	Y	Y
Treated-Control Startup Groups FEs	Y	Y
Observations	1191267	1191267
Dyads	133198	133198
Groups of Treated-Control Startups	48237	48237
R2	0.129	0.123
Mean Outcome Variable	0.00187	0.00409

Notes: This table reports the results from estimating linear probability models for the likelihood that a startup i belonging to dyad ij is acquired in t by: i) a large foreign firm (column 1); and ii) a small foreign firm (column 2). *Peer Acq. by Foreign Firm$_i$* is an indicator that equals one if the peer j of a startup i is acquired by a foreign firm and zero otherwise. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a foreign firm. We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A3: List of prominent acquirers

Amazon
AOL
Apple
Broadcom
CA Technologies
Cisco
Dell
Dropbox
eBay
Facebook
General Electric
Google
Hewlett-Packard
IBM
Intel
Lucent Technologies
Miscrosoft
Mitsubishi
Medtronic
Merck
Monsanto
Motorola
Nielsen
Oracle
Palo Alto
PayPal
Qualcomm
STMicroelectronics
Stryker
Xerox
Yahoo!

Table A4: Distinguishing between startups in their earlier and later stages

	Acquired by Foreign Firm (1)
Post Acquisition$_{gt}$	0.00799***
	(0.000692)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00184***
	(0.000498)
Late Stage$_{it}$	-0.00648**
	(0.00270)
Late Stage$_{it}$ $\times$ Post Acquisition$_{gt}$	0.0201***
	(0.00401)
Peer Acq. by Foreign Firm$_i$ $\times$ Late Stage$_{it}$	0.000515
	(0.00156)
Late Stage$_{it}$ $\times$ Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00452***
	(0.00152)
Dyad FEs	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y
Treated-Control Startup Group FEs	Y
Observations	1191267
R2	0.126

Notes: This table reports the results from estimating a linear probability model for the likelihood that a startup is acquired by a foreign firm in year t. We assess how the effect of the treatment varies depending on whether an observed startup i is in its early or later stages. We identify a startup as being in its later stages if it has raised at least a second round by t. The regressor of interest is the interaction between the *Late Stage*$_{it}$, *Peer Acq. by Foreign Firm*$_i$, which is an indicator that equals one if the peer j of a startup i is acquired by a foreign firm, and *Post Acquisition*$_{gt}$, which is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a foreign firm. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A5. Startup liquidity events after a peer is acquired by a foreign company: Adding time-varying controls

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by Foreign Firm	(4) Acquired by Israeli Firm
Post Acquisition$_{gt}$	0.0187***	0.0165***	0.0102***	0.00635***
	(0.000784)	(0.000747)	(0.000728)	(0.000657)
Peer Acq. by Foreign Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00420***	0.00454***	0.00359***	0.000955***
	(0.000513)	(0.000464)	(0.000456)	(0.000326)
Time Varying Controls	Y	Y	Y	Y
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y	Y	Y
Treated-Control Startup Group FEs	Y	Y	Y	Y
Observations	1191267	1191267	1191267	1191267
Dyads	133198	133198	133198	133198
Groups of Treated-Control Startups	48237	48237	48237	48237
R2	0.130	0.134	0.127	0.149
Mean Outcome Variable	0.01078	0.00959	0.00596	0.00363

Notes: This table reports the results from estimating linear probability models for the likelihood that a startup i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a foreign company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by Foreign Firm$_i$* is an indicator that equals one if the peer j of a startup i is acquired by a foreign firm and zero otherwise. *Post Acquisition$_{gt}$* is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a foreign firm. We control for: the cumulative amount of funds raised by i and j (and the corresponding interaction), the cumulative amount of US VC funds raised by i and j (including the interaction), and the cumulative number of US granted patents i and j applied for (including the interaction). We include fixed effects for: i) the ij dyad; ii) i's subsector-by-year; iii) j's subsector-by-year; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A6. Startup liquidity events after a peer is acquired by a US company

	(1) Acquisition/IPO	(2) Acquired	(3) Acquired by US Firm	(4) Acquired by US Firm
Post Acquisition$_{gt}$	0.0195***	0.0173***	0.00820***	0.00628***
	(0.000887)	(0.000847)	(0.000895)	(0.000827)
Peer Acq. by US Firm$_i$ $\times$ Post Acquisition$_{gt}$	0.00469***	0.00561***	0.00302***	0.00158***
	(0.000621)	(0.000558)	(0.000502)	(0.000348)
Dyad FEs	Y	Y	Y	Y
Year FEs $\times$ Obs. Startup Subsector FEs	Y	Y	Y	Y
Year FEs $\times$ Peer Startup Subsector FEs	Y	Y	Y	Y
Treated-Control Startup Group FEs	Y	Y	Y	Y
Observations	983062	983062	983062	983062
Dyads	104703	104703	104703	104703
Groups of Treated-Control Startups	35588	35588	35588	35588
R2	0.124	0.128	0.119	0.145
Mean Outcome Variable	0.01126	0.01003	0.00448	0.00371

Notes: This table reports the results from estimating linear probability models for the likelihood that a startup i belonging to dyad ij is: i) either acquired or goes public via an IPO in t (column 1); ii) acquired (column 2); iii) acquired by a US company (column 3); and iv) acquired by an Israeli company (column 4). *Peer Acq. by US Firm*$_i$ is an indicator that equals one if the peer j of a startup i is acquired by a US firm and zero otherwise. *Post Acquisition*$_{gt}$ is a time varying (0/1) indicator that becomes one for all the startups in a treated-control group g, after the peer j of a treated startup is acquired by a US firm. We include fixed effects for: i) the ij dyad; ii) a given year-i's subsector; iii) a given year-j's subsector; and iv) group g including a treated startup and its controls. Refer to the notes in Table 2 for a description of how the g groups are formed. Standard errors (in parentheses) are multi-way clustered by year and by groups of treated and control startups. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.