What is the US Comparative Advantage in Entrepreneurship? Evidence from Israeli Migration to the United States*

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Abstract

We investigate underlying sources of the US entrepreneurial ecosystem's advantage compared to other innovative economies by assessing the benefits Israeli startups derive from migrating to the US. Addressing positive sorting into migration, we show that migrants raise larger funding amounts and are more likely to have a US trademark and be acquired than non-migrants. Migrants also achieve a higher acquisition value. However, their patent output is not larger. We conclude that the US entrepreneurial ecosystem's advantage vis-à-vis other innovative economies arises from several sources producing sizeable gains for startups. These sources are investor availability, and large consumer and acquisitions markets.

1 Introduction

Entrepreneurial ecosystems play a fundamental role in spurring a country's employment, innovation, and economic growth (Glaeser *et al.*, 2015; Akcigit and Kerr, 2018). However, despite their

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acknowledged contribution, little is known regarding the factors that are responsible for their success (Moretti, 2012). The United States (US), for example, holds a similar ranking in education and innovation as other developed economies. Yet, its entrepreneurial ecosystem is considered to be relatively more successful.[1] Indeed, every year a substantial number of startups from highly-innovative economies relocate their headquarters to the US, raising the question of what advantages the US entrepreneurial ecosystem offers relative to these economies.

One possibility is that the comparative advantage of the US entrepreneurial ecosystem arises from sources that transcend the country's level of education and innovation. Possible sources include a large consumer market (Krugman, 1991)—especially when comparing the US to other small innovative economies—the availability of specialized inputs (Marshall, 1920), the presence of investors (Chen *et al.*, 2010), and a developed market for acquisitions (Gans and Stern, 2003). This paper takes a first step toward shedding light on the underlying sources of the US entrepreneurial ecosystem's advantage relative to other innovative economies.

To do so, we use a novel dataset of 2,179 Israeli startups and evaluate the benefits they derive from establishing their headquarters in the US (which we refer to as "migration"). Our empirical context is appealing for two reasons. First, Israel has historically built strong ties with the US and Israeli startups regard the US as an attractive destination, thereby making migration to this country a frequent event rather than an outlier (Senor and Singer, 2009). In our sample, for instance, 13% of the startups established their headquarters in the US, while none of them opened headquarters in Europe. Second, Israel shares a specialization in similar industries as the US, suggesting that the skills valued in the US and in Israel are comparable. This is an important prerequisite for attributing any observed migration effect to differences in resources between Israel and the US

[1] See for instance: `http://paulgraham.com/america.html`.

(Borjas, 1987).

We begin our empirical analysis by evaluating the startups' decision to establish their headquarters in the US. We document positive sorting into migration showing that, compared to non-migrants, startups that establish their headquarters in the US raise larger amounts of funds during their first financing round, are more likely to attract US venture capitalists (VCs), and, be founded by successful serial entrepreneurs. Migrants are also more likely to have applied for US granted patents and trademarks. A machine learning model predicting approximately 70% of the variation in the startup likelihood of migrating to the US confirms positive sorting into migration. This model additionally shows that Israeli startups with a high predicted likelihood of migrating to the US are successful even when they do not actually migrate. This result is reassuring, as it suggests that it is possible to find a valid counterfactual to migration among startups remaining in Israel.

We next delve into the core of our analysis and investigate the gains Israeli startups derive from migrating to the US. We explore six startup performance outcomes that closely map onto some of the most relevant migration benefits we mentioned earlier. We first examine whether startups apply for a trademark with the US Patent and Trademark Office (USPTO) to assess the benefits of penetrating a larger consumer market. We then analyze the number of US patents startups apply for to evaluate the advantages of accessing innovation inputs localized in the US. We also examine the amount of venture capital (VC) raised to gauge the gains migrants derive from a relatively large supply of US investors. Finally, we evaluate the likelihood that a startup is acquired and the likelihood that it experiences an initial public offering (IPO), as well as its transaction value in the case of an acquisition. These last three measures allow us to assess whether migrants derive benefits from accessing a larger market for exits.

Our challenge is that failure to control for startup heterogeneity biases migration estimates upward. We adopt three approaches to address this concern. First, we implement a double-LASSO regression.[2] While LASSO is a widely used method for the regularization of high-dimensional data, the concern is that it may be suited for prediction but not for inference. To address this problem, we implement a "double"-LASSO algorithm, applying a first LASSO selection procedure to predict startup migration and a second LASSO to retain the largest predictors of the startup performance outcomes (Belloni *et al.*, 2014a). The union of the observables obtained from these two procedures constitutes the set of controls in the performance equations. This double selection method has been shown to produce valid inference even when certain relevant variables are excluded (Belloni *et al.*, 2014a, 2014b).

Second, we compare migrants' outcomes to those of startups that, for plausibly exogenous reasons, find it costly or impossible to migrate. The latter are startups operating in the defense sector and that conduct stem cell research. The defense sector is characterized by strict regulations that prevent Israeli startups operating in this sector from migrating to the US market. Similarly, there are considerable restrictions on embryonic stem cell research in the US as compared to Israel (Furman *et al*., 2012), reducing the profitability of migrating to the US for startups developing technologies in this field. Conditional on our observables, we show that these startups represent an unbiased control group for movers. Our final approach consists of estimating a startup fixed-effects model exploiting across migrant variation in migration age.

The results are consistent across models. We find that migrants are significantly more likely than non-migrants to apply for a trademark in the US. Migrants also raise more VC, particularly from US VCs, and experience a greater likelihood of being acquired, especially by US companies. Additionally, upon an acquisition, migrants' sales value is higher. The significance of these effects

[2]LASSO stands for Least Absolute Shrinkage and Selection Operator.

is confirmed after employing the Oster (2019) bounding method, which allows us to establish lower bounds for our migration effects: all these bounds are above zero. We do not find any significant migration effect on the likelihood that startups will experience an IPO, although Israeli migrants are more likely to go public on the US stock exchanges and less likely to go public on the Tel Aviv Stock Exchange. Similarly, we find that migration produces no significant effect on the number of patents Israeli startups apply for.

The significant effects we find are economically important. Our estimates indicate that startups that move by age 3 are 14 to 26 percentage points more likely to apply for a trademark with the USPTO and raise 36% to 111% more VC funds than non-migrants. Additionally, migrants are 17 percentage points more likely to be acquired than non-migrants, and their acquisition value is 100% higher. These effects are largest for startups that establish their headquarters in the US instead of opening a subsidiary, and for those that migrate to California, Massachusetts, and the New York area.

Our findings provide important insights for policy makers investing resources to build entrepreneurial ecosystems and, in particular, for those policy makers from countries that try to emulate the US model (Lerner, 2009). Specifically, our results suggest that to build a successful entrepreneurial ecosystem policy makers should broaden the scope of their investments beyond education and innovation.

This paper primarily builds on the economic geography and entrepreneurship literatures. The first strand of the literature has highlighted the importance of factors such as market size (Krugman, 1991), access to specialized inputs (Marshall, 1920), and information spillovers (Audretsch and Feldman, 1996) in explaining the clustering of economic activities in certain regions of the world. We transpose these factors into the specific entrepreneurship context and identify those responsible for the relative success of the US entrepreneurial ecosystem and the startups it hosts. In doing so, we rely on studies that have investigated the determinants of entrepreneurial clusters (Chinitz, 1961; Saxenian, 1994; Glaeser and Kerr, 2009; Glaeser *et al.*, 2010a; Glaeser *et al.*, 2010b) to specifically focus on underlying sources of the US entrepreneurial ecosystem's comparative advantage. Finally, our results speak to the literature that has analyzed the differences in productivity levels between the US and other countries. In particular, our finding that migration produces no significant patent gains stands in contrast to the findings of Bloom *et al.* (2012), who have shown that Americans "do IT better." Israel hosts a large pool of highly skilled individuals, especially in information and communication technology (ICT), which reduces the relative benefits of migrating to the US for the specific purpose of achieving productivity gains.

2 Empirical Context: Israel, "The Startup Nation"

Israel is one of the world's most prolific innovative economies (OECD, 2018). An important share of Israeli innovations is produced by domestic startups (Bresnahan *et al.*, 2001). In the past three decades, Israel has given rise to one of the most vibrant entrepreneurial clusters outside of the US, hosting the largest number of technology startups per capita worldwide (The Economist, 2014). Many of these startups operate in ICT, reflecting Israel's specialization in this area, although they have recently expanded to other sectors (Beyar *et al.*, 2017). The country's successful efforts in building a startup ecosystem have earned Israel the title "Startup Nation". This success has been largely ascribed to a combination of factors, including Israel's military service, a large availability of scientists and engineers, and *ad hoc* government policies (Trajtenberg, 2000).

Israelis go through several years of compulsory military service, which provides them with training in military technologies that can lead to relevant commercial applications, especially in

ICT sectors. The technical training Israelis receive is particularly intense in elite army units, such as Unit 8200. Individuals selected for these units have produced technologies at the forefront of the fields of wireless communications, IT networks, the internet, and data security, among others. These elite units are not only responsible for developing their members' technical skills, but also for providing them with important business-related experience. Admitted individuals manage projects that very much resemble those pursued in high-technology startups. Another determinant input is the large availability of scientists and engineers, which is reflected in Israel's top ranking in the per capita number of individuals with a Science, Technology, Engineering and Mathematics degree (Beyar *et al.*, 2017). Renowned research institutions, such as Technion, and the large influx of Soviet Jews that followed the dissolution of the USSR, have greatly contributed to the creation of this human capital stock. Finally, it is also important to mention the active role the Israeli government plays in sustaining private R&D projects, particularly those undertaken by startups. A significant government initiative is the creation of Yozma, a type of venture fund with the goal of stimulating other venture funds, and the establishment of a number of high-technology incubators and R&D subsidy programs (Conti, 2018).

While there is little doubt that Israeli entrepreneurs benefit from domestic R&D spillovers, they operate in a small market. As a result, they have traditionally looked to the US market as the preferred destination for their technologies, and many of them have opened a subsidiary in the US or even established their headquarters there. Although Israeli entrepreneurs are, in general, attracted to the US market, some of them run companies that are prevented from establishing headquarters in the US. These include companies operating in the defense sector and those developing stem cell, particularly embryonic stem cell, technologies. The international mobility of firms in the defense sector has traditionally been low. Israel is no exception. To prevent the leakage of information related to strategic technologies, Israeli legislation prohibits the overseas transfer of defense know-how unless individuals obtain an appropriate license from the Director General of the Ministry of Defense or the Head of the Defense Export Control Agency.[3] This regulation hinders the migration to the US of Israeli startups operating in the defense sector, especially considering that relocation licenses are rarely granted. Regarding startups developing embryonic stem cell technologies, the Bush administration introduced restrictions on research conducted with embryonic stem cells in August of 2001, imposing severe limitations on federal funding (Furman *et al.*, 2012). Relatedly, it is noteworthy that while the Christian religion considers that a person comes into existence at the time of conception, thus making it unacceptable to conduct research on an embryo at any stage of development, the Jewish Law gives priority to born human life over human life in development and, moreover, does not ascribe human dignity to an embryo outside of the uterus. Thus, Israel admits and subsidizes the creation of embryos for scientific purposes (Levine, 2008). Overall, both the US restrictions on funding for embryonic stem cell research and the differences in religious approaches over the beginning of life increase the Israeli startups' costs of moving to the US.

3 Dataset

We build our dataset from Conti (2018) and extend it by employing additional sources of information derived from the Israel Venture Capital Research Center (IVC).[4] Conti (2018) complemented the IVC data with information on both US granted patents that Israeli startups applied for and grants awarded from the Israeli Office of the Chief Scientist. We enrich this original dataset with information on startup migration as well as trademark applications with the USPTO. Descriptive

[3] `http://www.shibolet.com/the-export-and-licensing-of-defense-technologies-part-i/`.
[4] Conti *et al.* (2013a) and Conti (2018) describe the details of the sample construction.

statistics are reported in Table 1.[5]

The startups in the dataset were founded between 1990 and 2014. Israeli startups predominantly operate in ICT sectors, reflecting Israel's comparative advantage in these areas. Moreover, the majority of startups were initially established in the area around Tel Aviv, where most of the high-technology companies are concentrated.

Approximately 19% of the startups filed for a US granted patent in the founding year or the year after. This figure increases to 34% when we examine a five-year window from inception. Twelve percent of the startups have a university connection, meaning that they were either established by a professor or received support from a university Technology Transfer Office (TTO). Altogether, these figures highlight that a considerable share of our startups are high-technology companies.

The average funding amount startups raised during their first round is \$1.48 million.[6] The funding distribution is skewed and the median value is only \$0.4 million. Twenty-four percent of the startups received VC investment during their first round and 7.2% obtained funds from US VCs.[7] Regarding exits, 113 (5%) of the startups experienced an IPO as of 2014, and 494 (23%) an acquisition. Of the acquired startups, 66% had a US acquirer. The average sales upon an acquisition is \$78 million and increases to \$89 million when the acquirer is a US company.[8] Taken together, these data provide an indication of the relevance of US investors for Israeli startups. Following an established literature (Castaldi, 2019), we use data on trademark applications to the USPTO to measure the extent of Israeli startups' penetration in the US product market. Of the total companies, 8.5% had applied for at least one trademark in the US during the inception year or the

[5]Table A1 reports descriptive statistics by migrant status and temporal period.

[6]Of the startups' initial rounds, 94% are "seed" rounds. The remaining 6% have at least one Israeli investor.

[7]IVC classifies institutional investors into: VCs, private equity firms, investment banks, insurance companies, pension funds, and advisory & management companies. While many non-VC investors manage venture capital funds or funds of similar nature, we take a conservative position and exclude them from our category of VCs.

[8]Exit values are only available for 373 of the 494 acquired companies.

year after. The percentage increases to 21 when considering a five-year window from inception.

Migration data

We use business registration records from US states to determine whether Israeli startups migrated to the US. These public records are created when a firm is registered as a corporation, partnership, or limited liability company with the Secretary of State (or Secretary of the Commonwealth) of any US state.[9] We use the date of registration as the date of migration. According to the rules, companies must register at least two distinct addresses in each state: the address of the principal office and the address of the office within the state. This distinction allows us to differentiate between Israeli startups that establish their headquarters in the US and those that open a US-based subsidiary (such as a sales office) while maintaining their headquarters in Israel. To complement our data and verify existing information we employ secondary sources of information, such as Crunchbase, LinkedIn, company websites, and newspaper records of startups' relevant events. In our main analysis, we define as migrants only those startups that established their headquarters in the US and not those companies that opened a US-based subsidiary.

Two hundred ninety startups relocated their headquarters in the US, while 96 startups opened a subsidiary. More than half of the migrants (60%) established their headquarters within the first 3 calendar years of their inception, with the remaining scattered across subsequent years. We restrict our definition of entrepreneurial migrants to consider only those that moved within three years of being founded. As a result, we remove 114 startups from the sample.[10] We remove two startups that the data suggest moved at ages -2 and -3, but keep three startups that moved at age -1. The clustering of migrants in their early years is consistent with US evidence provided in

[9]Other studies have used these data, including Guzman and Stern (2016) and Guzman and Stern (2017).

[10]Though this cutoff of three years is admittedly *ad hoc*, we adopt it because we are specifically interested in the location choices startups make during their earliest years. Our results are robust to adopting different cutoffs.

Guzman (2018). While the US appears to be an attractive migration destination, our secondary sources show that none of the startups in our sample opened headquarters in Europe and only 59 companies opened a branch in this region.

Migrants operate mostly in ICT sectors and are predominantly from the Tel Aviv district. A large share of them (53%) established their headquarters in California, a destination that matches well with Israel's comparative advantage in ICT.[11] Figure 1 depicts the distribution of first-round VC financing for startups that established their headquarters in the US versus those that did not move. As shown, migrants raise on average larger financing rounds than non-migrants. Figure 2 depicts a series of startup characteristics, distinguishing by migrant status. This figure shows that migrants: i) are more likely to have a US VC participate in their first round of financing than non-migrants (Panel A); ii) filed relatively more patents (Panel B) and trademarks (Panel C) with the USPTO during the founding year or the year after; iii) are more likely to be acquired (Panel D) and, conditional on being acquired, sell at double the amount of non-migrants (Panel E); and iv) experience IPOs more frequently than non-migrants, although IPOs are relatively rare in general.

4 The selection of Israeli startups into migration

We begin our empirical analysis by examining the differences across Israeli startups in their likelihood of migrating. This analysis will help guide the implementation of a machine learning algorithm for predicting the likelihood of moving to the US and addressing selection concerns.

We initially estimate a logit model relating our observables to the likelihood of migrating to the US. The results are presented in Table 2, which reports incidence rate ratios (IRRs) and standard errors clustered at the founding-year level. In column (1), we assess the relationship between the

[11] Figures A1 and A2 show the distribution of migrants by migration age, destination, sector, and founding location.

amount of financing a startup raised during its first round and the likelihood of migrating to the US. The IRR is 3.13, implying that a one log-point increase in the amount of funds raised is associated with a 213% increment in the likelihood of migrating. The predictive power of this variable is remarkably high, producing a pseudo R^2 of 0.11. To the extent that a startup's initial financing is indicative of future performance, this result suggests strong positive sorting.

In column (2), we include a measure of the founders' human capital, that is, the number of successful startups they initiated in the past. The effect of an extra successful startup is 44%. The pseudo R^2, 0.02, is lower than the 0.11 figure at the bottom of column (1), suggesting that the predictive power of this variable is not as high as that of the size of a startup's first financing round. Column (3) examines: i) whether a company had applied for at least one US granted patent during the start year or the year after, and ii) whether a company had applied for at least one trademark with the USPTO during the same period. Startups with at least one successful patent application and those with at least one trademark application are 61% and 127% more likely to migrate to the US. However, the pseudo R^2 remains considerably lower than the one reported in column (1).

In column (4), we include all the controls and add sector as well as founding year fixed effects. The impact of the funding amount a startup received on migration remains large and highly significant relative to the effect reported in column (1). In contrast, the IRRs associated with the patent and trademark measures are no longer statistically significant. This last result should not be surprising, given that VCs have been found to invest in startups possessing intellectual property rights (Conti *et al.*, 2013b; Catalini *et al.*, 2018). There is substantial sector variation in the likelihood of migrating. In particular, startups operating in IT and software are the most likely to migrate to the US. In column (5), we include an indicator identifying those startups that raised US VC funding during their first round. As shown, the IRR is 4.1, indicating that startups supported by US VCs are 310% more likely to move to the US. While this effect is large, the coefficients of the other variables change little from those reported in column (4), suggesting that the information embedded in the US VC indicator only partially overlaps with that conveyed by the other variables.

Overall, these results highlight three relevant patterns. First, there is positive assortative matching, whereby migrants are startups with the greatest potential. Second, the examined measures of startup potential are correlated with one another and with other relevant startup aspects. Finally, the specific characteristics of VCs participating in the startups' earliest financing round play a significant role in the companies' migration choice, and this role transcends the amounts VCs invest.

A machine learning model for predicting the likelihood of migrating

Because the insights above suggest that there could be many factors predicting a startup's choice to move, we develop a machine learning model to select those observables with the largest predictive power. To implement this model, we compile a list of covariates including the startup selection characteristics controlled for in Table 2 as well as additional variables reported in Table 1. Once this list is generated, we create two-way interactions among all the observables to account for the possibility that their relationship with the migration outcome is either non-linear or contingent on certain startup characteristics. Finally, we construct fixed effects for each of the investors participating in a startup's first round of financing. In doing so, we address the possibility that differences in individual investors' characteristics or the strategies they envisage for their portfolio startups may drive the selection into migration. Expanding our initial dataset in these directions generates 1,392 variables. As a next step, we prune the observables using LASSO (Tibshirani, 1996). This "regularization" algorithm addresses the problem of overfitting inherent to high-dimensional data. The coefficients are chosen to minimize the sum of squared residuals plus a penalty term that penalizes the size of the model through the sum of absolute values of the coefficients. The implementation of LASSO leads us to retain 110 out of the original 1,392 variables.

We employ this set of variables in a random subsample of our data, which maintains 60% of the initial observations (N=1,307), to train a random forest model (Breiman, 2001) for predicting the likelihood of migrating to the US. We then repeat this train/test procedure 49 times with newly extracted random samples of the same size as the original one.

Table A2 shows the top 50 variables by their average "feature importance", which reflects the variables' predictive power. Individual investor fixed effects are strong predictors of a startup's likelihood of migrating, suggesting that investors play an important role in either selecting startups with a high *ex ante* likelihood of migrating or inducing their investee startups to migrate. None of the sector fixed effects appear in the list, suggesting that the selected investor fixed effects disproportionately capture investor preferences for certain sectors.

We test the performance of our model by examining the Receiver-Operating-Characteristic (ROC) score, which is a measure of the model's ability to separate between true negatives and true positives. Larger values of this score are associated with higher chances that the model will correctly classify each startup as either migrant or non-migrant. We compute the ROC score for the 40% (N=872) observations we had initially excluded in the training of the random forest. The aim is to assess the out-of-sample predictive power of the model. The results are encouraging. As shown in Figure 3, both the median and the mode ROC scores are equal to 0.84, a large value on a scale from 0.5 (completely uninformative model) to 1 (fully informative model). This value implies that our model accounts for approximately 70% of the variation in the data.[12]

Figure 4 reports the share of startups that experienced a liquidity event over the percentile

[12] We obtain a similar distribution when we employ subsector rather than sector fixed effects. The results are reported in Figure A3, while the list of subsectors is in Table A3.

distribution of the predicted probability of migration, obtained from the machine learning model. Panel A considers the entire sample of startups, while Panel B only examines the subset of non-migrants. As shown, startups with a high predicted probability of migrating are more likely to exit successfully, regardless of whether they actually migrate to the US or not. The positive correlation between the startups' predicted probability of migrating and success that we observe in Panel B suggests that it is possible to find a valid counterfactual to migration among non-migrants.

5 The US entrepreneurial ecosystem's comparative advantage

Having examined the factors determining sorting into migration, we move on to estimate the migration benefits Israeli startups derive from establishing their headquarters in the US. We begin by outlining our empirical strategies, and then discuss the main results and heterogeneity analyses.

5.1 Empirical strategies

We estimate the relationship between migrating and the performance of those startups that choose to migrate to the US. Ideally, to identify migration effects on startup performance outcomes, we would estimate the treatment effect on treated companies, τ, which is defined as:

$$\tau = E[Y_i(1) - Y_i(0)|D_i = 1] \tag{1}$$

where $Y_i(1)$ indicates startup i's performance if it establishes its headquarters in the US, $Y_i(0)$ denotes i's performance if it remains in Israel, and D_i is an indicator that is equal to 1 if startup i migrates and 0 otherwise. The fundamental empirical challenge we face is that $Y_i(0)$ is unobserved for the movers, which requires us to estimate $Y_i(0)$ from the information we have available. A naïve approach would regress the performance outcomes of startups on whether they migrate to the US or not. Comparisons between migrants and non-migrants based on this approach are likely to be upwardly biased given the positive sorting we documented in Section 4. Thus, we adopt a number of alternative approaches that exploit both startup cross-sectional and panel data.

Double LASSO on high-dimensional data. Our first approach consists of implementing a double-LASSO model. As we mentioned earlier, LASSO is an appealing method for estimating the parameters of a sparse high-dimensional linear model (Belloni *et al.*, 2014b). However, using this method to select the best predictors of startup performance outcomes may prevent causal inference to the extent that LASSO drops controls that are highly correlated with the treatment on the ground that these controls do not add much predictive power for the outcome of interest. To address this problem, we estimate a "double"-LASSO algorithm wherein we apply a first LASSO to the selection equation that predicts startup migration to the US and a second LASSO to retain the largest predictors of the startup performance outcomes. The union of the observables obtained from these two procedures represents the set of variables we control for in the performance equations. Belloni *et al.* (2014a) show that this double selection procedure can lead to valid inference even when selection mistakes occur and certain relevant variables are excluded. The first LASSO, which we described in Section 4, led us to select 110 of the 1,392 high-dimensional covariates derived from expanding our initial set of observables. The high ROC scores obtained suggest that we are able to explain a large portion of Israeli startup selection into migration. Since we examine multiple startup performance outcomes, we repeat the second LASSO procedure as many times as the number of performance outcomes we consider.[13]

Quasi-experiment exploiting plausibly exogenous institutional constraints on a startup's ability to migrate. As we mentioned in Section 2, Israeli startups operating in the defense and embryonic stem cell domains are prevented from establishing their headquarters in the US. Specifically, startups in the defense sectors face moving restrictions imposed by the Israeli government. Similarly,

[13]The second step of the double-LASSO selects an average of 49 covariates.

startups developing embryonic stem cell technologies suffer from restrictions on US federal funding, while no such restrictions are imposed in Israel. In our quasi-experiment, we employ the startups operating in these sectors as counterfactual to those companies that, instead, are not restricted by government regulations and migrate to the US. After a careful analysis of the startup technology descriptions provided by IVC, we identified 32 companies operating in the defense domain and 14 companies developing embryonic stem cell technologies. Defining S_i as an indicator for whether a company belongs to the control group of startups that cannot migrate, we estimate the treatment effect on the treated as follows:

$$\hat{\tau} = \hat{E}[\hat{E}[Y_i|D_i = 1, p_i] - \hat{E}[Y_i|S_i = 1, p_i]] \tag{2}$$

where $\hat{\tau}$ is the estimated average treatment on the treated. To guarantee the comparability of treated and control startups, we restrict our sample to those treated and control startups (N=126) that are in the region of common support as determined by p_i, that is, the predicted probability of migrating obtained from the random forest model described in Section 4. The distribution of p_i for each group of treated and control startups is presented in Figure A4.

The key assumption here is that the composition of the control group is orthogonal to a startup's performance, conditional on p_i. Under this assumption, the performance of the control group can be considered an accurate estimate of the migrants' performance, had they kept their headquarters in Israel. One concern is that the government-regulated sectors we have identified would have been relatively secluded from the US market even in the absence of government restrictions. For instance, Israeli startups in the defense sector may predominantly produce technologies for the domestic market and these technologies could be incompatible with foreign standards. Similarly, Israeli startups developing embryonic stem cell technologies may be specialized in addressing domestic rather than US market needs. Overall, these unobserved barriers could introduce a spurious positive correlation between founders' propensity to migrate and their startups' performance. However, Israeli defense companies are intensive exporters, and one of their largest destination markets is the US (The Jerusalem Post, 2019). Likewise, Israeli embryonic stem cell companies have frequent collaborations with US firms and research institutions (Luo and Matthews, 2013).

A related concern is that individuals with an intrinsically high propensity to migrate refrain from operating in sectors affected by government restrictions and, instead, self-select into sectors where migration to the US is less costly. To the extent that the individuals' propensity to migrate to the US is correlated with their entrepreneurial skills, the migration effects obtained from estimating Equation (2) would be upwardly biased. However, here we note that Israeli founders' technologies are often the by-product of training imparted in specialized army units. As Perman (2004) points out, the selection process into these units very much resembles the process of "NBA scouts tracking kids in high school and college," leaving limited discretion to recruits. Moreover, within these specialized units, the technologies that conscripts develop are highly influenced by Israeli army needs, further reducing future founders' discretion. Similarly, founders commercializing technologies developed during their university studies, as it is often the case for embryonic stem cell technologies, are unlikely to have enrolled in specific tertiary education programs in anticipation of institutional constraints on their ability to relocate overseas. Admission into these programs depends on a large number of factors, including individuals' secondary school performance and the score they obtained in the Psychometric Entrance Test, as well as the availability of advisors and their funding, in the specific case of graduate programs.

Another concern may be that VCs, and especially foreign VCs, avoid investing in certain sectors because startups in these sectors are prevented from accessing the US consumer and exit markets. To evaluate this issue, Table A4 reports relevant predetermined startup characteristics, distinguishing by migrant status and conditioning on the common support region. Reassuringly, these characteristics do not significantly differ between migrants and non-migrants. Among them is whether startups received US VC funding.

To further support our strategy, we compare several performance outcomes of "quasi-exogenous" stayers with those of non-exogenous stayers, that is, those stayers belonging to "non-restricted" subsectors. If our strategy were valid, then the former category of stayers should outperform the latter. Consistently, Table A5 shows that stayers in the “restricted” subsectors outperform the other stayers across a large range of outcomes. Although these tests provide reassuring results, we opt to control for p_i, which is the predicted probability of migrating obtained from the random forest model described in Section 4.[14]

Panel Regressions. Finally, we exploit within-migrant variation of performance outcomes over time by estimating the following regression for each startup i of age t moving at age m:

$$Y_{i,t,m} = \alpha_t + \gamma_m + \beta D_{i,t} + \lambda_i + \varepsilon_{i,t,m} \tag{3}$$

where α_t denotes age fixed effects, γ_m designates age of migration fixed effects, $D_{i,t}$ is an indicator equal to 1 if an Israeli startup had its headquarters in the US at age t (and zero otherwise), λ_i are startup fixed effects, and $\varepsilon_{i,t,m}$ is a random noise. The coefficient of interest is β which captures the within-startup improvement in performance after a company moves to the US. In this model, the age of migration fixed effects address the potential concern that there are systematic differences among startups migrating at different ages. This approach is useful for capturing startups’ invariant characteristics, such as founders’ "chutzpah" (i.e. audacity), which the literature has mentioned as one factor being positively correlated with Israeli startups’ performance (Senor and Singer, 2009).

[14]Specifically, we include as regressors in Equation (2) the natural logarithm of p_i and its squared term.

To assess how the benefits from migrating vary over a startup's life cycle, we estimate a variant of Equation (3) adding interactions between $D_{i,t}$ and startup age indicators:

$$Y_{i,t,m} = \alpha_t + \gamma_m + \delta_t \alpha_t D_{i,t} + \lambda_i + \varepsilon_{i,t,m} \tag{4}$$

5.2 Results

We explore the relationship between migrating to the US and six startup performance measures. These measures closely map onto the most relevant types of migration benefits startups could derive by establishing their headquarters in the US. The first measure is an indicator for whether a startup applied for a trademark with the USPTO after *t+1*, where *t* is the founding year. This indicator captures startup gains from penetrating a market larger than the domestic economy. The second measure is the number of US granted patents startups applied for after *t+1*, which captures the advantages of accessing innovation inputs localized in the US. The amount of VC raised after the first funding round proxies the gains migrants may derive from accessing a comparatively large supply of investors. Finally, we consider the likelihood that a startup will be acquired and the likelihood that it will go public via an IPO, as well as the transaction value upon an acquisition. These are measures for the value startups could extract from their technologies after entering a relatively larger market for technology. In describing the results, we distinguish between startups' intermediary performance outcomes -that is, trademark, patent, and financing raised- and final exit outcomes.

5.2.1 Intermediary startup performance outcomes

The cross-sectional estimates of the migration effects on the startups' intermediary performance outcomes are displayed in Table 3. We estimate ordinary least squares (OLS) regressions for each outcome. Moreover, we report the results obtained from the following three estimation models.

Model I is a naïve model that includes only an indicator identifying startup migrants. *Model II* refers to the double-LASSO model, while *Model III* is the quasi-experiment we mentioned in Section 5.1. *Model I* and *Model II* control for founding year and subsector fixed effects (listed in Table A3), while Model III controls for founding year fixed effects. To account for any correlation in the error terms within founding year and sector, *Model I* and *Model II* double-cluster standard errors by founding year and sector. In *Model III*, we bootstrap standard errors given that the control p_i is derived from the entire sample and not just from the subset considered for the quasi-experiment.

Column (1) of Table 3 reports the migration results for the likelihood that a startup applies for a trademark registration with the USPTO. According to the naïve model, migrants are 36 percentage points more likely to apply for a US trademark *ex post* than non-migrants; the coefficient is significant at the 1% level. The double-LASSO model predicts that migrating to the US translates into a 26 percentage point increased likelihood of applying for a US trademark.[15] The relatively smaller coefficient is consistent with the positive sorting into migration we documented in Section 4. The migration effect remains significant when we examine our quasi-experimental sample. This effect is larger than the one obtained from the double-LASSO. Indeed, it is obtained from a subset of the distribution of startups, and particularly the subset with a relatively low *ex-ante* probability of migrating.

Column (2) of Table 3 displays migration effects on startup patent output. The naïve model estimates a positive and significant effect of migrating on patents. However, the effect loses its sig-

[15] We find similar results when the double-LASSO considers subsector fixed effects in the variable selection process of both the selection and treatment equations (Table A6). Additionally, we find similar results when we estimate a Coarsened Exact Matching (CEM) model and generate a synthetic control group of stayers that matches treated startups on sector, founding year, the amount of VC funding raised in the first round, whether a US VC invested in a startup's first round, and whether a startup had applied for a US granted patent at inception (Table A7).

nificance and diminishes in magnitude with both the double-LASSO specification and our quasi-experimental sample. In moving from the naïve to the double-LASSO specification, the magnitude of the effect declines by approximately 88%. This finding suggests that Israeli migrants do not derive significant benefits from accessing innovation inputs localized in the US. As such, this finding confirms the fact that Israel hosts a large supply of highly-skilled individuals, which diminishes the relative importance of achieving innovation productivity gains as a reason for moving to the US. Indeed, several startups maintain their R&D centers in Israel when they migrate.

Column (3) presents the effects of migrating to the US on the amount of VC funding that startups receive. As expected, the naïve model considerably overestimates the effect of moving to the US. However, after addressing selection concerns with both our double-LASSO and quasi-experimental approaches, we continue to find significant migration effects on the amount of VC financing. In particular, we show that migrants raise at least 93% more VC than non-migrants. Finally, in column (4), we assess whether the gains startups derive in VC financing are led by US VCs. As shown, migrants raise 110% more US VC than non-migrants in the double-LASSO model, while the estimate from the quasi-experimental sample is 128%. The magnitudes of these effects are similar to those reported in column (3), supporting the conjecture that Israeli startups migrating to the US derive positive gains from that country's comparatively large investor market.

Table 4 reports the panel results from estimating equations (3) and (4). Here, we exploit within-mover variation to assess changes in migrants' performance after they establish their headquarters in the US. We limit the sample to the first seven years of a startup's life cycle to focus on the initial, entrepreneurial stages of a startup, rather than on those follow-on, more consolidated, stages. We examine the same outcome variables as in Table 3. A startup's trademark and patent outputs, as well as the amount of funds raised, are cumulative from inception. *Model I*, in the upper part of

Table 4, uses an indicator (*Has Moved*) that takes on value 1 starting from the year a startup establishes its headquarters in the US and zero in the pre-migration period. Therefore, the coefficient of this indicator represents the *average* variation in performance that migrants experience after they establish their headquarters in the US. *Model II*, in the lower part of Table 4, introduces interaction terms between the *Has Moved* indicator and startup age dummies. The coefficients of these interactions capture the effect of having moved by a given age on startup performance outcomes. In all models, we double-cluster standard errors by founding year and sector.

Column (1) of Table 4 examines the trademark measure. Focusing on *Model I*, the coefficient of *Has Moved* is positive and significantly different from zero at conventional levels. The magnitude of the effect suggests that moving to the US increases the likelihood that a startup will have applied for a trademark by 8 percentage points. *Model II* reveals an interesting pattern. By age 4, migrants are 15 percentage points more likely to have registered a trademark with the USPTO than non-migrants, and the magnitude of the difference remains approximately the same for later years.

Column (2) of Table 4 reports the results for over-time variation in a migrant's rate of patenting. Consistent with our cross-sectional results, we find that the coefficient of the *Has Moved* indicator is approximately zero in *Model I*. Moreover, the results from *Model II* show that none of the coefficients for the interactions between *Has Moved* and the different startup ages are significant and all their magnitudes are approximately zero. Collectively, these results confirm that Israeli startups establishing their headquarters in the US do not derive significant innovation productivity gains.

Columns (3) and (4) examine the cumulative amount of VC financing Israeli startups raised over time. Column (3) considers the totality of a startup's cumulative VC amount, while in column (4) we analyze cumulative funding, taking into account only those rounds led by a US VC. *Model*

I shows that a startup raises significantly more financing after migrating, regardless of whether we cumulate all the round amounts (column (3)) or only those led by US VCs (column (4)). The results from *Model I* indicate that, after migrating, startups receive, on average, 30% more financing and 45% more US VC financing. The results from *Model II* reported in column (3) suggest that these migration effects are relatively smaller during a startup's inception, accelerate later on, and finally decline after age 2, although they generally remain statistically significant. The only exception is the effect for companies that have moved by age 6. These companies do not raise significantly more funds than companies that have moved by age 7. However, we note that most of the Israeli migrants' acquisitions occur before age 7. Regarding the cumulative funding raised from US VCs (column (4)), the magnitudes of the migration effects increase with a startup's age and remain large even during the company's later years. Starting from age 2, these magnitudes are substantially larger than those reported in column (3) for the total cumulative amount of funding raised.[16] Overall, our panel analyses confirm the cross-sectional findings. Israeli startups migrating to the US derive significant gains from penetrating a comparatively large consumer market and accessing a wide availability of investors. At the same time, we continue to find that Israeli migrants do not significantly improve their innovation productivity.

While our three approaches to dealing with positive selection into migration deliver consistent results, one may still be worried that our findings are the result of selection rather than of the migration treatment. To further address this concern, we follow Oster (2019) and compute a lower bound for our migration effects to assess whether they can be convincingly bounded away from zero. The results are displayed in Table A9. In each column, the baseline specification con-

[16]The results remain qualitatively similar when we examine the yearly VC amount raised rather than the cumulative amount. The results are reported in Table A8.

trols for founding year and sector fixed effects, while the expanded specification includes all the double-LASSO controls. Despite the fact that the expanded specification adds important startup aspects such as VC fixed effects, which make the R-squared increase by at least 73% once they are included, the migration effects decline by at most 31%. Consequently, the lower bounds of our estimates are all above zero. Moreover, the reported measure, δ, for the relative degree of selection on observed and unobserved variables suggests that the influence of unobservables relative to observables would need to be over 2.8 times larger to produce a null migration effect. This last scenario is unlikely given the predictive power of our machine learning model.[17]

Exploring the mechanisms of our financing results. Tables 3 and 4 reported that Israeli startups raise more funding upon migrating. This result could be explained by Israeli startups attracting a larger number of investors after they migrate. Alternatively, it could be driven by the fact that investors located in the US have greater financial means than other investors. We explore these conjectures in Table 5, where we present estimates for the number of unique investors that have funded a startup after its first round of financing, *having controlled for the total funding amount the startup raises* during the same period. We present our cross-sectional models in Table 5.[18]

The results reveal an interesting pattern. While the number of unique investors is positively correlated with migration (column (1)), the migration coefficient drops when we control for the amount of funding a startup raises and the point estimate becomes negative (column (2)). However, when we consider the number of US investors only (column (3)), the coefficient of migration re-

[17] McKenzie *et al*. (2010) find that empirical models identifying migration effects using matching models tend to overstate migration gains by approximately 30%. As we mentioned, our machine learning model predicts approximately 70% of the variation in the startups' likelihood of migrating to the US. While the remaining 30% could be due to selection, it could also be ascribed to other factors, such as randomness or measurement error. Even if we postulated a 30% overstatement of migration gains, the true migration effects would still be considerably larger than the lower bounds we found with our more stringent version of the Oster (2019) method.

[18] Unreported panel results are consistent with the cross-sectional findings in Table 5.

mains positive and statistically significant, even after controlling for the amount of funding raised. Upon migrating, Israeli startups increase their portfolio of US investors by at least 0.5. As shown in columns (4) and (5), this result is driven specifically by US VCs (column (4)) rather than by other types of US investors (column (5)). Finally, the results reported in column (6) reveal that startup migrants attract fewer non-US investors than non-migrants, all else being equal. The magnitude of the coefficients suggests that migrants attract 1 fewer non-US investor than startups maintaining their headquarters in Israel. Collectively, the findings presented in Tables 3 to 5 suggest that Israeli migrants substitute non-US with US VCs after they move and raise larger amounts of funding as a consequence.

5.2.2 Startup exit outcomes

We now move on to assess the impact of migrating to the US on these companies' exit performance. Table 6 reports the cross-sectional results. As before, *Model I* and *Model II* control for founding year and subsector fixed effects, while Model III controls for founding year fixed effects. Moreover, *Model I* and *Model II* double-cluster standard errors by founding year and sector, while in *Model III* standard errors are bootstrapped. Column (1) reports the migration results for the likelihood of exiting via an acquisition. Relative to non-migrants, companies moving to the US are 17 percentage points more likely to be acquired under the double-LASSO approach. Considering that 21% of the startups in our sample have been acquired, this effect is economically large.[19] In the quasi-experimental sample, we similarly find that migrants are 40 percentage points more likely to be acquired than stayers.

We next explore whether these results are driven by the comparatively large US supply of acquirers or by an increase in startup productivity following migration. To shed light on this point,

[19]Results in Table A10 and obtained from estimating a Cox proportional hazards model confirm this finding.

column (2) reports migration results for the likelihood that a startup is acquired by a non-US company. If the size of the US market for acquisitions were a relevant determinant of the Israeli startups' decision to migrate, then Israeli migrants should be more likely to be acquired by US companies than by foreign ones. Consistent with this hypothesis, the results in column (2) show that either Israeli migrants are less likely than non-migrants to be acquired by non-US companies (*Model II*) or migration does not affect the likelihood that a startups is acquired by a non-US firms (*Model III*).

Column (3) reports the effects of migrating to the US on startups' sales values upon acquisition. The estimates are sizable. Relative to stayers, startups moving to the US experience a 100% and a 195% increase in sales value, depending on whether we follow the double-LASSO or the quasi-experimental approach. These results suggest that acquirers respond to Israeli startups migrating to the US along both the intensive (likelihood of acquiring) and extensive (sales price) margins.

Remarkably, we find that establishing headquarters in the US does not significantly affect the likelihood that a startup will go public via an IPO (column (4)), the point estimate being approximately zero. In Table A11 of the Appendix, we delve deeper into this finding by distinguishing between those IPOs that took place on the US stock exchanges and those that occurred on the Tel Aviv Stock Exchange (TASE). The results presented in columns (2) and (3) provide some suggestive evidence showing that Israeli migrants are more likely to go public on the US stock exchanges than non-migrants. However, migrants appear less likely than non-migrants to go public on the TASE (column (3)). The totality of these findings suggests that, while Israeli startups moving to the US may show a preference for the US stock exchanges, their overall probability of experiencing an IPO does not increase.[20]

[20]Table A12 shows that migrants are, overall, less likely to go bankrupt than non-migrants.

We next discuss the panel regression results, which we present in Table 7. As before, we include startup fixed effects and exploit within-mover variation to assess the change in migrants' performance after they establish their headquarters in the US. We also include startup-age and age-of-migration fixed effects. We examine the same startup performance outcomes as in Table 6, except for a startup's sales price, which cannot be analyzed in a panel format.

The panel results confirm our cross-sectional findings. Column (1) of Table 7 examines the likelihood that a startup will have been acquired by a given year. Upon establishing their headquarters in the US, Israeli migrants become, on average, 6 percentage points more likely to have exited via an acquisition (*Model I*). Consistent with the fact that the gains from moving gradually accumulate over time, *Model II* reports a steady increase in the probability that a startup will have experienced an acquisition by a given year. A startup that moved by age 6 is 26 percentage points more likely to have exited through an acquisition. Column (2) reports the results for the likelihood that a startup will have been acquired by a non-US company. The point estimate derived from *Model I* is small in magnitude (0.003), suggesting again that acquisition gains from moving to the US are positively correlated with the availability of US acquirers. The results from *Model II* support this conjecture. Except for startups at age 0, the coefficients of the interactions between the *Has Moved* indicator and a startup's age dummies are all approximately zero or negative and mostly insignificant. Finally, column (3) reports the results for the likelihood that a startup will have exited through an IPO. Migrants are less likely to have experienced an IPO after moving to the US, and this difference, which is rather small, is consistent across the various startup ages.

To deal with the concern that our approaches may not completely address the non-random section into migration, we again perform the Oster (2019) bounding method and report the results in Table A13. As shown, the lower bounds of our migration effects are all greater than zero.

Exploring the mechanisms of our acquisition results. A concern with these findings is that the migrants' improved likelihood of exiting via an acquisition and increased sales value may not imply a US comparative advantage in hosting a large market for acquisitions. In fact, the evidence we provide could be consistent with the US hosting a relatively large market of VC investors who invest larger funding amounts than Israeli investors. As migrants receive relatively large funding amounts, they may become more attractive to potential acquirers and, thus, improve their likelihood of being acquired. Similarly, since a startup's sales value also reflects the startup's total capital, more funding would translate into a higher sales value. These examples illustrate that the size of the US market for acquisitions may not be an independent source of the US comparative advantage in entrepreneurship, but only a manifestation of a developed investor market.

We perform three complementary analyses to mitigate this concern. First, we estimate a modified version of the double-LASSO model presented in Table 6 controlling, this time, for the total amount a startup raised from US investors.[21] The results in Table A14 continue to show that migrants are more likely to be acquired than non-migrants, especially by US acquirers. In particular, migrants are 14 percentage points more likely to be acquired and 22 percentage points more likely to be acquired by US acquirers. These effects are similar in magnitude to those in Table 6 and Table A13, lending support to the interpretation that an important advantage of the US entrepreneurial ecosystem relative to other innovative economies is the larger market for acquisitions.

To further corroborate this interpretation, we estimate an instrumental variable (IV) model with panel data, which closely follows Freyaldenhoven *et al.* (2019). This approach consists of instrumenting a time-varying control with the leads of the treatment to remove the effect of the confounding factor of interest. The approach requires a time-varying covariate that i) is likely

[21] We additionally control for the total number of US granted patents and for whether a startup had a US trademark.

to be affected by the confounder -and therefore exhibits a pre-trend-, 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 number of investors participating in a startup's rounds as the time-varying covariate and instrument it with the first lead of the treatment. As we show in Panel A of Figure A6, the cumulative number of investors exhibits an increasing pre-trend. Therefore, it satisfies condition i). Moreover, as reported in Table 5, this variable is positively correlated with the migration treatment in the uncontrolled regression, but becomes uncorrelated with this treatment once we control for the amount of funds raised. Since this result suggests that migrants do not attract more investors than non-migrants, but have different investors participating in their rounds, the cumulative number of investors reasonably satisfies condition ii). Additionally, the finding confirms that our time-varying covariate is strongly correlated with the amount of funds raised, which is the confounding factor we worry about. The IV results are reported in Table A15. Consistent with our earlier findings, the effect of migrating on the cumulative likelihood that a startup will have been acquired by t is positive and significant. This effect continues to be driven by the acquisition of Israeli startups by US firms. Reassuringly, the pre-trends reported in Panel B of Figure A6 are jointly insignificantly different from zero with a p-value of 0.61.[22]

We finally focus on a startup's sales price upon an acquisition. We condition the sample to startups that were acquired by US companies and relate their sales value to whether they had migrated to the US. In this estimation, we control for the amount of funding the startups raised through exit, a squared term of this variable, an indicator for whether the startups raised US VC funding

[22]They were insignificantly different from zero with a p-value of 0.38 in the within-migrant OLS model.

during their first round, the total number of unique US VC investors participating in the financing of the startups, and the squared term of the latter measure. The rationale is to examine a homogenous sample of acquired startups and assess whether, within this sample, migrants improve their transaction value once we control for the amount of funding they raised and the characteristics of their investors. To mitigate possible selection concerns, we further control for whether startups had applied for a US granted patent or a trademark at founding, for whether startups are university spinoffs, for whether they have spent time in a government-sponsored incubator, and for the number of founders. We also include founding year, subsector, and founding location fixed effects. The results are reported in Table 8. We show that, among startups acquired by US companies, migrants experience at least a 76% increase in sales value relative to non-migrants, all else equal. The significance of this effect does not vary with the set of controls we employ in the regressions (less stringent in column (1) and progressively more stringent in columns (2) and (3)).

Overall, this evidence provides an indication that the US market for acquisitions represents an independent source of the US comparative advantage in entrepreneurship. In fact, the significance of this source persists even after controlling for the startups' funding characteristics.

5.3 Heterogeneity of migration responses

To bring our analysis full circle, we explore heterogeneity in startup performance response to migration. To increase the precision of our estimates and allow for comparisons across coefficients, we present the results from the double-LASSO models that use the full sample of startups.

5.3.1 Establishing headquarters in the US versus opening a branch office

We first explore heterogeneity in migration effects by contrasting the Israeli startups that choose to establish their headquarters in the US with those that decide to open a branch, using the Israeli startups that do not migrate as a benchmark. While some of the benefits that startups opening a branch in the US capture may be similar to those of startups establishing their headquarters in the US, others may vary depending on the startups' chosen migration type.

Table A16 reports the results. When analyzing the likelihood that a startup files for a trademark with the USPTO as an intermediary outcome, we find that the effect of establishing headquarters in the US is larger than the effect of opening a branch (column (1)). Examining the rate of patenting, instead, reveals that none of the coefficients associated with the different startup migration types is significantly different from zero (column (2)). Moving to startup financing, the funding amount that Israeli startups opening headquarters in the US raise is 47 percentage points larger than the amount raised by startups opening a branch (column (3)). This difference increases to 59 percentage points when we only consider funding amounts raised from US VCs (column (4)).

We next present the results for startups' equity outcomes. Israeli startups establishing their headquarters in the US are 12 percentage points more likely to be acquired than startups opening a US branch (column (5)). This finding stems from acquisitions by US companies (column (6)). Among acquired startups, those with headquarters in the US sell at a higher price than those opening a US branch (column (7)). The effect of migrating to the US on a startup's sales price is circa 88 percentage points larger if the startup establishes its headquarters in the US as opposed to opening a branch. Further, startups opening a US branch are more likely to go public via an IPO than companies establishing their headquarters in the US relative to the reference category of non-movers (column (8)). This last result, combined with the evidence presented in Table A11, suggests that for startups that open a branch in the US, the Israeli IPO market is a relevant source of financing. Collectively, these results confirm that the comparative advantage of the US entrepreneurial ecosystem stems from multiple sources. However, startups' ability to access several of these sources depends on whether they establish their headquarters in the US or open a branch.

5.3.2 Destination locations within the US

We finally examine whether there is any heterogeneity in migration benefits depending on the US location Israeli startups choose. We differentiate between the California (CA), Massachusetts (MA), and New York area (NY) destination locations, on the one hand, and the remaining US locations, on the other. We adopt this distinction to isolate the specific contribution to the US entrepreneurial ecosystem's comparative advantage of these startup clusters versus other US regions. The results are reported in Table A17. There is no considerable difference in effects between migrating to CA/MA/NY and moving to another US destination, with respect to the following startup performance outcomes: whether or not startups applied for a trademark with the USPTO (column (1)), the number of US patents a startup applied for (column (2)), and the likelihood of exiting via an acquisition or an IPO (columns (5), (6), and (8)). However, we observe a remarkable difference in effects when we examine the total (and US) amount of funding startups raise, and the sales price at which they are sold. Startups located in CA/MA/NY raise at least 109% more funds than non-migrants, while the increase for startups located in other states is only 59% and insignificantly different from zero (column (3)). This gap becomes wider when we only consider startup rounds led by US VCs (column (4)). Moreover, the price at which acquired startups located in CA/MA/NY are sold is at least 104% higher than the price at which acquired non-migrants are sold (column (7)). Conversely, the effect of migrating to US states other than CA/MA/NY on sales price is negative. Overall, the sources of the US comparative advantage are predominantly concentrated in those geographical areas that best characterize the US entrepreneurial ecosystem.

6 Concluding remarks

This paper uncovers the underlying sources of the US entrepreneurial ecosystem's advantage relative to other innovative economies. We do so using a rich dataset of Israeli technology startups and estimating the benefits these companies derive from establishing their headquarters in the US. We show that migrants are significantly more likely than non-migrants to have a trademark registered in the US. They are also more likely to raise VC funds and to be acquired. Moreover, conditional on experiencing an acquisition, migrant startups are sold at a higher price than non-migrant startups. These effects are not only statistically significant but also economically relevant. We do not find significant migration effects on the number of patents startups produce, suggesting that Israeli startups do not move to the US in order to improve their innovation output. The totality of these results lead us to conclude that, compared to other innovative economies, the US entrepreneurial ecosystem offers a multiplicity of advantages which generate sizeable gains for startups. The advantages we highlight are a large consumer market, high investor availability, and a developed market for acquisitions. As the entrepreneurial culture and investor ecosystem in Israel are more developed than in other innovative economies, the effects we find are likely to represent a lower bound of the gains innovative economies may derive from establishing a presence in the US.

Our findings have implications for those countries creating or expanding their startup ecosystems. They suggest that to attract high-growth startups, policy makers should broaden the scope of their investments and not just focus on bolstering their workforce education and level of innovation. For instance, countries like France, Germany, Italy, and Switzerland have a highly educated labor force that has generated salient innovations. Notwithstanding the domestic availability of innovation inputs, the most promising European startups do migrate to the US. In fact, widespread opinion holds that European countries lack both a network of investors, which provide funding opportunities as well as mentoring, and firms interested in acquiring new ventures. Moreover, despite the Single Market, the European consumers' market remains highly fragmented. The implication of our findings for these countries is that the creation of a startup ecosystem requires a comprehensive effort to enhance the marginal contribution of domestic innovation inputs by expanding complementary upstream and downstream markets of investors, acquirers, and consumers. This comprehensive effort has ultimately led Israel to retain, despite its small size, several promising startups.

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Figure 1: First-round VC financing distinguishing between migrants and non-migrants

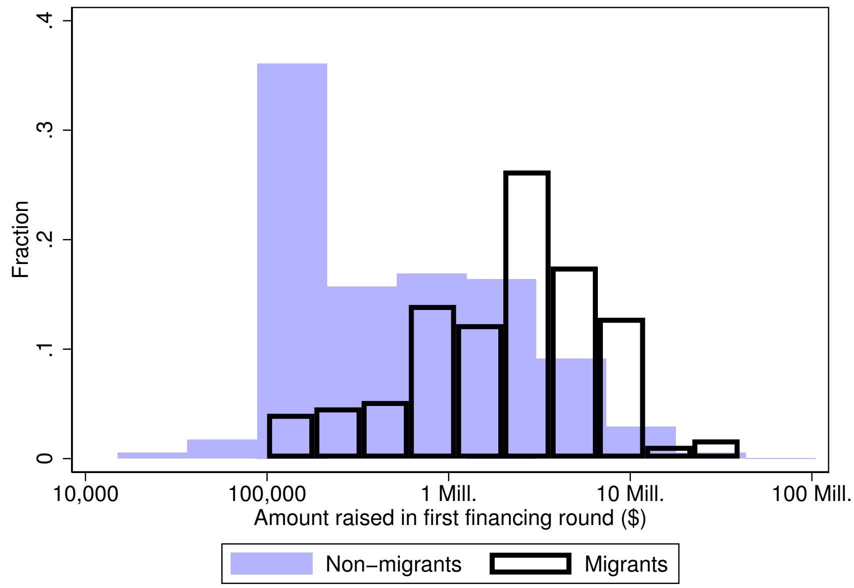
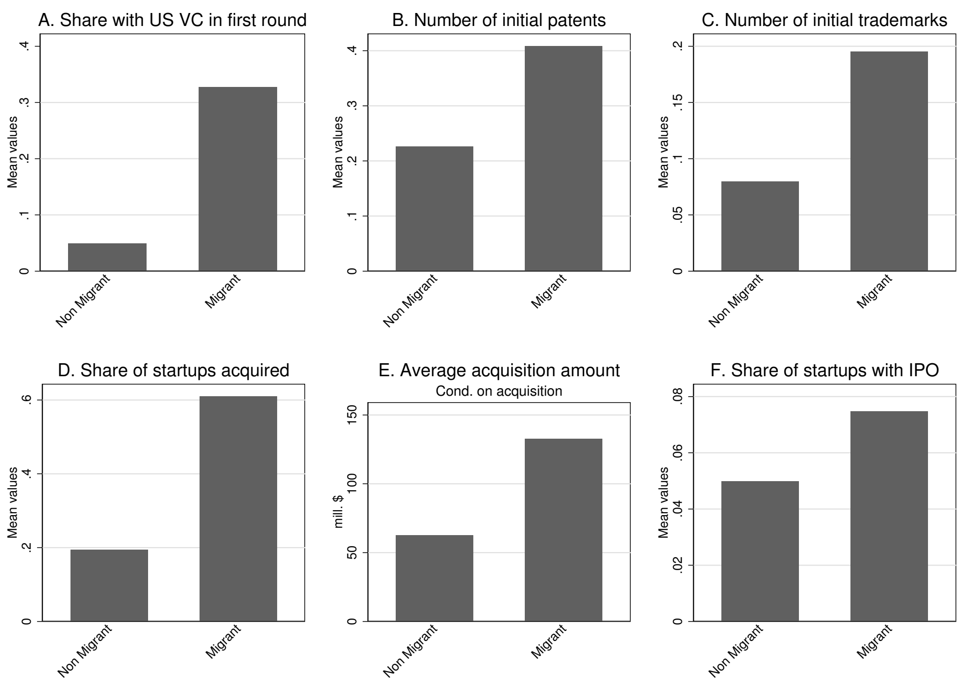
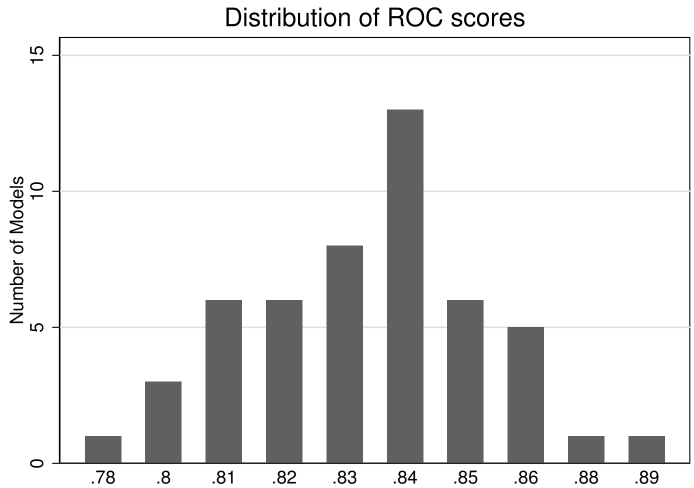


Figure 2: Mean values of startup characteristics distinguishing between migrants and non-migrants



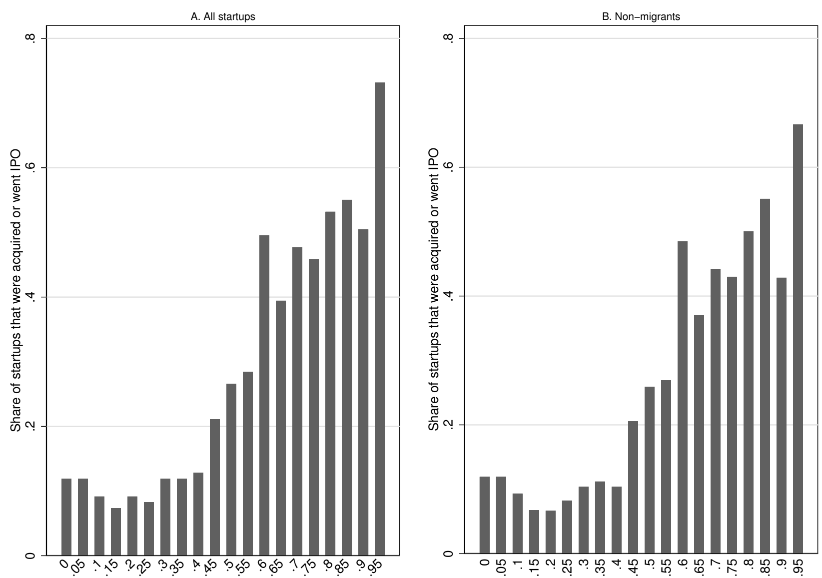
Notes: This figure depicts the distribution of startup characteristics at around founding time (Panels A-C) and performance outcomes (Panels D-F) by migrant status. Both startup characteristics and performance outcomes vary substantially between migrants and non-migrants.

Figure 3: Out-of-sample performance of the machine learning model predicting selection into migration



Notes: This figure assesses the performance of the machine learning model described in Section 4. We plot the distribution of the ROC scores derived from 50 random forest models, each trained with a random sample of 60% of the data (1,307 observations).

Figure 4: Performance of Israeli startups by their predicted probability of migrating to the US



Notes: This figure examines startup selection into migration. The x-axis reports the percentile distribution of the predicted probability of migration obtained from the machine learning model described in Section 4. Startups that are more likely to migrate are also better performers (Panel A). We show a similar pattern in Panel B, where we specifically consider the subsample of non-migrants.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	N
Human Capital			
Num. Prior Successful Startups	0.277	0.803	2179
Num. Founders	2.009	1.073	2179
University T.T.O. Investment (0/1)	0.007	0.083	2179
University Spinoff (0/1)	0.118	0.323	2179
Has Funding from Israeli Chief Scientist (0/1)	0.145	0.353	2179
Initial Intellectual Property			
Initial Num. of Patents	0.241	0.605	2179
Has Initial Patents (0/1)	0.190	0.391	2179
Initial Num. US Inventors	0.187	1.310	2179
Initial Num. Israeli Inventors	1.051	5.018	2179
Has Initial Trademarks (0/1)	0.085	0.279	2179
First Round Financing			
Financing in First Round (mill. $)	1.484	3.664	2179
First Round Has US VC (0/1)	0.072	0.258	2179
First Round Num. of VC Investors	0.372	0.786	2179
First Round Num. of Corp. VC Investors	0.021	0.147	2179
First Round Num. of Angel Group Investors	0.025	0.163	2179
First Round Num. of Insurance Company Investors	0.001	0.037	2179
First Round Num. Private Equity Investors	0.019	0.139	2179
First Round Num. Bank Investors	0.001	0.030	2179
First Round Num. US Investors	0.171	0.493	2179
First Round Num. US VCs	0.091	0.366	2179
First Round Num. Non-Israeli Investors	0.265	0.638	2179
First Round Num. Israeli Investors	0.773	0.891	2179
First Round Num. Non-Israeli VC	0.114	0.412	2179
First Round Num. Israeli VC	0.257	0.604	2179
Sector			
Clean Tech (0/1)	0.078	0.268	2179
Communication Technology (0/1)	0.163	0.37	2179
IT / Software (0/1)	0.214	0.410	2179
Internet (0/1)	0.158	0.365	2179
Life Sciences (0/1)	0.121	0.326	2179
Medical Devices (0/1)	0.127	0.333	2179
Miscellaneous (0/1)	0.091	0.287	2179
Semiconductor (0/1)	0.048	0.213	2179
Founding Location			
Haifa (0/1)	0.089	0.286	2179
North (0/1)	0.093	0.290	2179
Center (0/1)	0.330	0.470	2179
West Bank (0/1)	0.006	0.08 0	2179
Jerusalem (0/1)	0.066	0.248	2179
Tel Aviv (0/1)	0.371	0.483	2179
Other Startup Characteristics			
Individual Investor Fixed-Effects			
Second Order Polynomials			
Two-Way Interactions			
Founding Year			
Migration			
Moves to US (0/1)	0.08	0.271	2179
Age at Migration	1.052	1.022	174
Performance Outcomes			
Total Amount Raised (mill. $)	9.067	19.974	2179
Total Amount Raised, Round Led by US VC (mill. $)	3.708	14.365	2179
Acquired (0/1)	0.227	0.419	2179
Acquired Outside US (0/1)	0.076	0.265	2179
Acquisition Value (mill. $)	77.98	128.89	373
IPO (0/1)	0.052	0.222	2179
Final Applied for Trademark (0/1)	0.240	0.427	2179
Final Num. of Patents	2.751	21.382	2179
Final Num. Investors	3.595	3.677	2179
Final Num. US Investors	0.648	1.441	2179
Final Num. US VCs	0.336	0.933	2179
Final Num. Non-US Investors	2.948	2.905	2179

Notes: Descriptive statistics for the observables of our sample startups. The word "initial" refers to a startup's founding year (t) and the year after ($t+1$). The word "final" refers to the years following $t+1$ and up to 2014.

Table 2: Who migrates? Determinants of Israeli startup migration to the US. Logit regressions. D.V.: Moves to US

	(1)	(2)	(3)	(4)	(5)
Ln(First round amount mill. $ +1)	3.128***			2.809***	2.230***
	(0.402)			(0.396)	(0.345)
Num. Prior Successful Startups		1.437***		1.234**	1.193*
		(0.0815)		(0.0827)	(0.0890)
Has Initial Patents			1.613**	1.295	1.227
			(0.290)	(0.342)	(0.351)
Has Initial Trademarks			2.270***	1.070	1.092
			(0.532)	(0.282)	(0.236)
First Round Has US VC					4.096***
					(1.197)
Clean Tech				0.0594**	0.0655**
				(0.0593)	(0.0649)
Communication Technology				0.370***	0.334***
				(0.0998)	(0.0882)
Semiconductor				0.406*	0.444*
				(0.144)	(0.172)
Internet				1.099	1.163
				(0.241)	(0.263)
Life Sciences				0.336**	0.374*
				(0.127)	(0.160)
Medical Devices				0.177***	0.220***
				(0.0638)	(0.0753)
Miscellaneous				0.0364**	0.0442**
				(0.0402)	(0.0478)
Year F.E.	No	No	No	Yes	Yes
Observations	2179	2179	2179	2179	2179
Pseudo R^2	0.112	0.021	0.016	0.204	0.233
Log Likelihood	-538.6	-593.8	-596.8	-482.6	-465.5

Notes: We report the results from estimating logit models for the likelihood that an Israeli startup establishes its headquarters in the US. The regressors of interest are measures for a startup's performance potential. To build the patent and trademark indicators, we only consider patents and trademarks that were applied for during the founding year or the year after. We report incidence-rate ratios (IRRs). Ratios greater than one imply that an increase in the value of a given regressor leads to a higher likelihood that an outcome occurs, with the opposite for ratios less than one. Standard errors are clustered at the founding-year level to account for the possibility that the attractiveness of the US market to Israeli startups might have changed over time. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table 3: The effect of migrating to the US on Israeli startups' intermediate performance outcomes: Cross-sectional results

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC +1)	(4) Ln(VC +1) (US VC Led Only)
Model I: Naive (N=2179)				
Moves to US	0.357***	0.478***	1.686***	1.594***
	(0.0258)	(0.0284)	(0.0511)	(0.00908)
Model II: Double-LASSO (N=2179)				
Moves to US	0.256***	0.0597	1.112***	1.096***
	(0.0581)	(0.0879)	(0.107)	(0.128)
Model III: Quasi-Experiment (N=126)				
Moves to US	0.383***	0.263	0.927***	1.280***
	(0.0877)	(0.180)	(0.232)	(0.272)
R2 Model I	0.0515	0.0213	0.115	0.167
R2 Model II	0.264	0.506	0.463	0.406
R2 Model III	0.418	0.213	0.398	0.334

Notes: This table reports the estimates for the impact of migrating on startup performance. We examine four intermediate outcomes. The first measure is an indicator for whether a startup applied for a trademark with the USPTO after *t+1*, where *t* is the startup's founding year (column (1)). The second measure is the number of US granted patents a startup applied for, again after *t+1* (column (2)). The third and fourth outcomes are the amount of VC raised after the first financing round (column (3)) and the amount of US VC raised during the same period (column (4)), respectively. Model I is the naive model described in the text. Model II is the double-LASSO. Model III is our quasi-experiment exploiting exogenous institutional constraints on the startup's ability to migrate. Model II controls for subsector and founding year fixed effects, while Model III only controls for founding year fixed effects. Standard errors (in parentheses) are double-clustered at founding year and sector levels for Models I and II, and bootstrapped for Model III. Significance denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The effect of migrating on Israeli startups' intermediate performance outcomes: Within-migrant variation

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC+1)	(4) Ln(VC+1) (US VC Led Only)
Model I: Main Difference				
Has Moved	0.0800**	0.00399	0.303***	0.448***
	(0.0329)	(0.0645)	(0.0957)	(0.0977)
Model III: Movers Across Age				
Age = 0 X Has Moved	-0.0540	0.0186	0.314***	0.193
	(0.0931)	(0.0836)	(0.110)	(0.245)
Age = 1 X Has Moved	0.0914*	-0.0294	0.384***	0.352***
	(0.0501)	(0.0644)	(0.0886)	(0.0914)
Age = 2 X Has Moved	0.102***	0.0215	0.511***	0.624***
	(0.0279)	(0.0531)	(0.0659)	(0.0780)
Age = 3 X Has Moved	0.135***	0.0528	0.357***	0.587***
	(0.0399)	(0.0760)	(0.127)	(0.0835)
Age = 4 X Has Moved	0.151***	0.0644	0.221*	0.593***
	(0.0394)	(0.101)	(0.126)	(0.0445)
Age = 5 X Has Moved	0.148***	0.0107	0.193*	0.630***
	(0.0436)	(0.129)	(0.105)	(0.101)
Age = 6 X Has Moved	0.152***	-0.00892	0.0764	0.611***
	(0.0428)	(0.152)	(0.103)	(0.0924)
Observations	16768	16768	16768	16768
R2 Model I	0.804	0.795	0.840	0.823
R2 Model II	0.807	0.796	0.843	0.824

Notes: This table reports the estimates for the impact of migrating on startup intermediary performance outcomes, exploiting within-migrant variation. We examine the same outcome variables as in Table 3. A startup's trademark (column (1)) and patent output (column (2)), as well as the amount of funding raised (columns (3) and (4)) are cumulative from founding. All regressions include startup fixed effects, age fixed effects, and age at migration fixed effects. Model I uses an indicator (*Has Moved*) that takes on value 1 starting from the year in which a startup established its headquarters in the US and zero in the pre-migration period. Model II introduces interaction terms between the indicator *Has Moved* and startup age dummies. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table 5: The effect of migrating on the number of unique total investors

	(1) Total Investors	(2) Total Investors	(3) Total US Investors	(4) Total US Investors (VC Only)	(5) Total US Investors (Non-VC)	(6) Total Non-US Investors
Model II:Double-LASSO (N=2179)						
Moves to US	1.656***	-0.413	0.520**	0.487***	0.0446	-0.967***
	(0.352)	(0.304)	(0.220)	(0.120)	(0.153)	(0.295)
Ln(VC+1)		2.460***	0.696***	0.364***	0.335***	1.767***
		(0.179)	(0.0775)	(0.0664)	(0.0269)	(0.187)
Model III: Quasi-experiment (N=126)						
Moves to US	1.528	-0.172	0.808***	0.535*	0.273*	-0.980
	(1.088)	(0.566)	(0.266)	(0.295)	(0.153)	(0.617)
Ln(VC+1)		2.234***	0.861***	0.439***	0.422***	1.374***
		(0.279)	(0.252)	(0.154)	(0.109)	(0.156)

Notes: This table reports the effects of migrating on the number of unique investors participating in the startups' financing rounds (starting from the second round), *having controlled for the total amount of funding raised.* In columns (1) and (2), we examine the total number of unique investors. In column (3), we consider the number of US investors as an outcome, while in column (4) we focus on the number of US VCs. In column (5), the outcome is the total number of US non-VC investors, while in column (6) we examine the total number of non-US investors. In all regressions, we include fixed effects for the number of unique investors participating in the startups' first round of financing. Model II includes founding year and subsector fixed effects, and Model III only founding year fixed effects. Standard errors (in parentheses) are double-clustered at founding year and sector levels for Model II and bootstrapped for Model III. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table 6: The effect of migrating to the US on Israeli startups' equity outcomes: Cross sectional results

	(1) Acquired	(2) Acquired by non-US firm	(3) Ln(Exit $)	(4) IPO
Model I: Naive (N=2179)				
Moves to US	0.416***	-0.0328*	1.134***	0.0248
	(0.0393)	(0.0169)	(0.170)	(0.0180)
Model II: Double-LASSO (N=2179)				
Moves to US	0.174**	-0.0692**	0.996***	0.0357
	(0.0733)	(0.0349)	(0.240)	(0.0413)
Model III: Quasi-Experiment (N=126)				
Moves to US	0.401***	0.000172	1.952	0.0111
	(0.0949)	(0.0494)	(1.266)	(0.104)
R2 Model I	0.0724	0.00112	0.0710	0.000922
R2 Model II	0.303	0.141	0.368	0.213
R2 Model III	0.293	0.355	0.137	0.190

Notes: This table reports the estimates for the impact of migrating on four startup equity outcomes. The outcomes are: the likelihood that a startup is acquired (column (1)), the likelihood it is acquired by a non-US company (column (2)), a startups' sales value (column (3)), and the likelihood it exits through an IPO (column (4)). Model I is the naive model described in the text. Model II is the double-LASSO. Model III is our quasi-experiment. Model II includes founding year and subsector fixed effects, and Model III founding year fixed effects. Model III in column (3) does not include founding year fixed effects given that the sample size is only 36 and the main effect cannot be identified. Standard errors (in parentheses) are double-clustered at founding year and sector levels for Models I and II, and bootstrapped for Model III. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table 7: The effect of migrating to the US on Israeli startups' equity outcomes: Within-migrant variation

	(1) Acquired	(2) Acquired by non-US Firm	(3) IPO
Model I: Main Difference			
Has Moved	0.0632	0.00300	-0.00974
	(0.0411)	(0.00790)	(0.0195)
Model III: Movers Across Age			
Age = 0 X Has Moved	-0.0425	0.0158*	-0.0131
	(0.0663)	(0.00839)	(0.0180)
Age = 1 X Has Moved	0.0172	0.0158	0.00664
	(0.0331)	(0.0109)	(0.0210)
Age = 2 X Has Moved	-0.000939	-0.000407	-0.0113*
	(0.0339)	(0.0137)	(0.00599)
Age = 3 X Has Moved	0.0626**	-0.00297	0.0129
	(0.0292)	(0.0142)	(0.0172)
Age = 4 X Has Moved	0.126***	-0.00994	-0.0118
	(0.0181)	(0.0136)	(0.0232)
Age = 5 X Has Moved	0.155***	-0.0223**	0.0151
	(0.0306)	(0.00865)	(0.0295)
Age = 6 X Has Moved	0.256***	-0.0115	-0.0289
	(0.0352)	(0.0116)	(0.0418)
Observations	16768	16768	16768
R2 Model I	0.539	0.451	0.432
R2 Model II	0.559	0.454	0.439

Notes: This table reports the estimates for the impact of migrating on three startup equity outcomes, exploiting within-migrant variation. Columns (1) and (2) examine a startup's acquisition events, while Column (3) assesses the likelihood that the startup will have exited via an IPO, as of a given year. All regressions include startup fixed effects, age fixed effects, and age at migration fixed effects. Model I uses an indicator (*Has Moved*) that takes on value 1 starting from the year in which a startup established its headquarters in the US and zero in the pre-migration period. Model II introduces interaction terms between the indicator *Has Moved* and startup age dummies. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table 8: The role of the market for acquisitions as a source of the US entrepreneurial ecosystem's comparative advantage - Controlling for venture capital financing in startups acquired by US companies

	(1) Ln(Exit $)	(2) Ln(Exit $)	(3) Ln(Exit $)
Moves to US	1.073***	0.785**	0.763*
	(0.255)	(0.232)	(0.324)
Ln(Total VC Raised +1)		0.287	0.137
		(0.181)	(0.268)
Ln(Total VC Raised +1)^2			0.0403
			(0.0487)
Has US VC in First Round			-0.305
			(0.406)
Ln(Total Unique US VC Investors +1)			0.173
			(0.311)
Ln(Total Unique US Non VC Investors +1)			-0.391
			(0.291)
Observations	242	242	242
R^2	0.303	0.324	0.358

Notes: This table reports regressions results for the impact of migrating to the US on the startups' acquisition price. We restrict the sample to startups acquired by US companies and control for multiple VC characteristics, and the financing amount received. All regressions include indicators for whether startups had applied for a US granted patent or a trademark at founding, for whether startups are university spinoffs, and for whether they spent time in a government-sponsored incubator. We also control for the number of founders and include founding year, subsector, and founding location fixed effects. The coefficient of *Moves to US* in column (3) can be suggestively interpreted the effect of the US market for acquisitions as a source of the US comparative advantage in entrepreneurship, having controlled for the role of VC financing. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Online Appendix

Figure A1: Number of migrants by age and US state destination

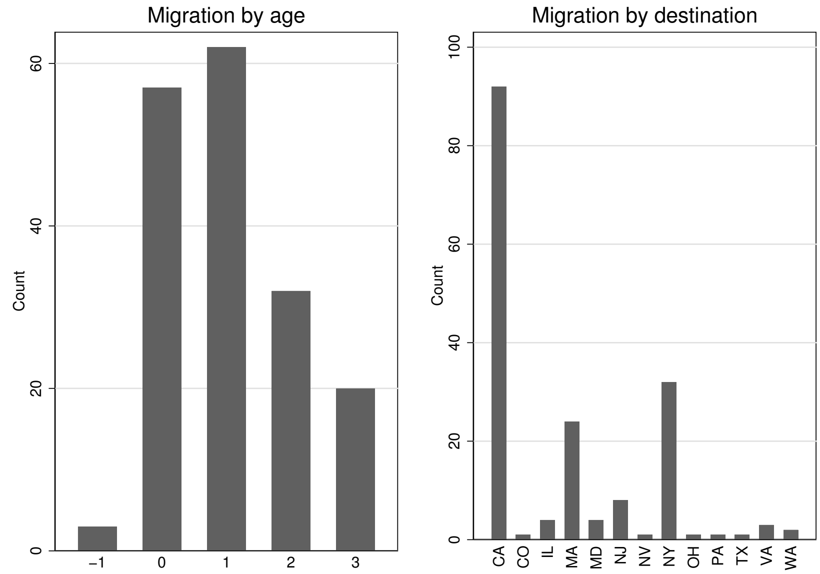


Figure A2: Sector and founding location of startup migrants

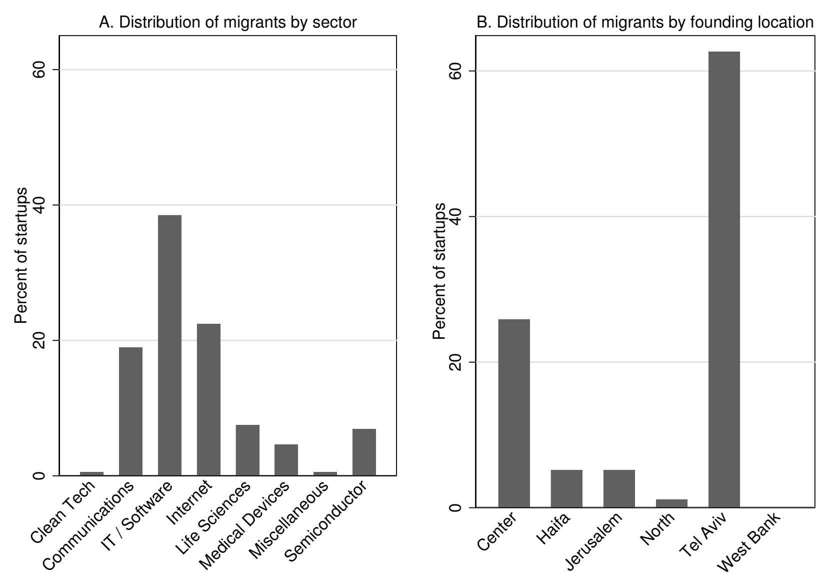
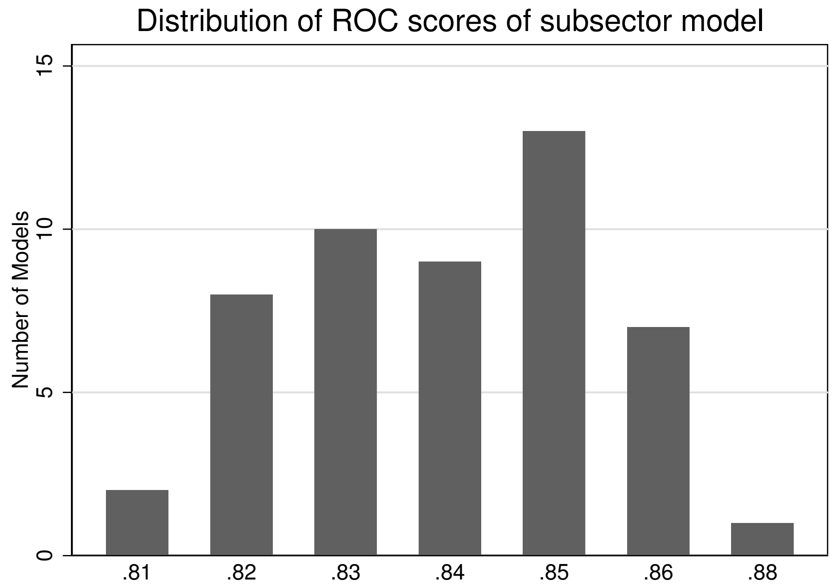
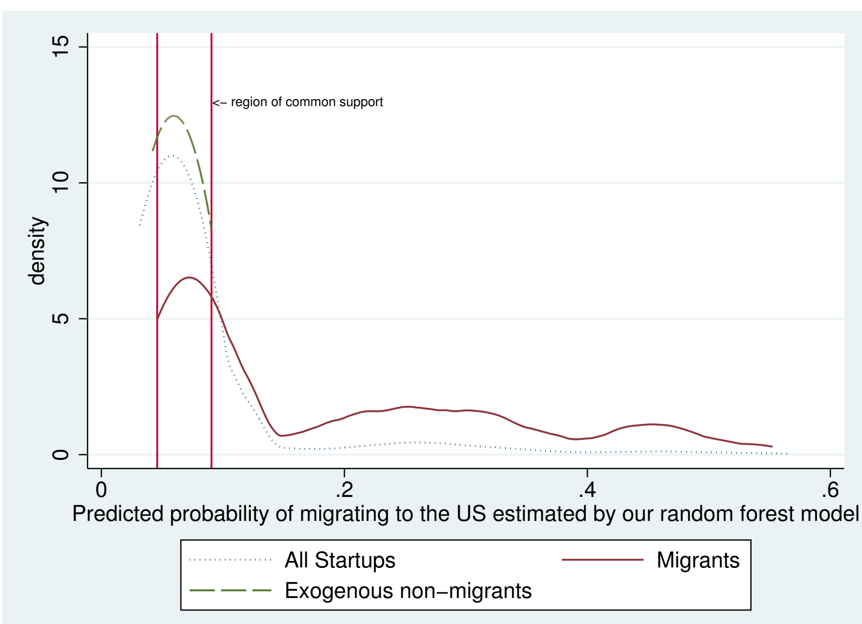


Figure A3: Out-of-sample performance of the machine learning model predicting selection into migration with subsector fixed effects



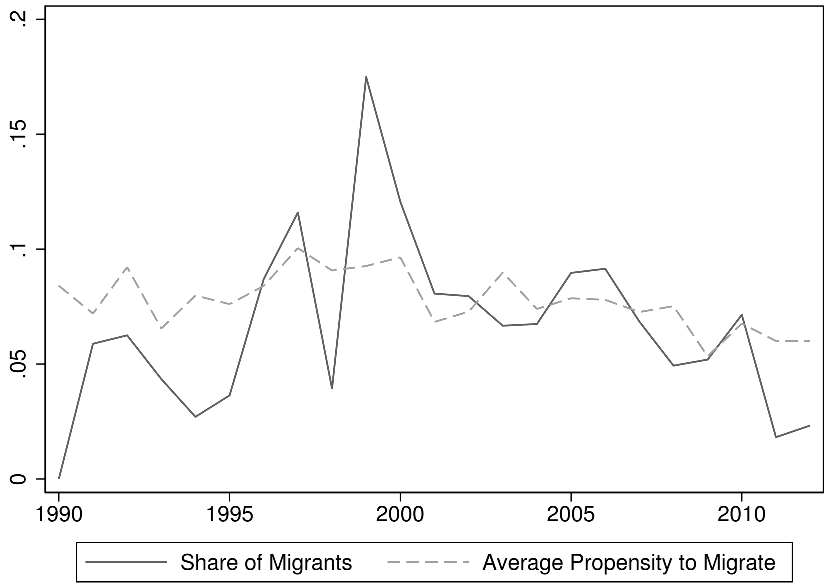
Notes: This figure assesses the performance of the machine learning model described in Section 4 after including subsector fixed effects. We plot the distribution of the ROC scores derived from 50 random forest models, each trained with a random sample of 60% of the data (1,307 observations).

Figure A4: Distribution of the predicted probability of migrating



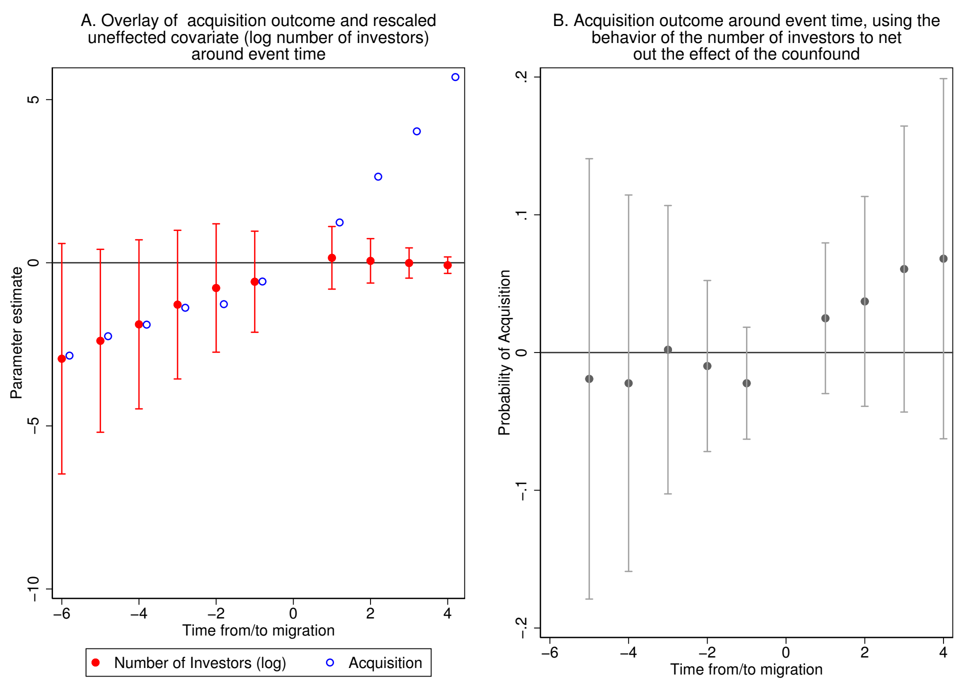
Notes: We plot the kernel distribution of the predicted probability of migrating to the US (estimated by the random forest model described in Section 4 for: i) all startups, ii) migrants, and iii) the set of exogenous non-migrants that we employ in our quasi-experiment.

Figure A5: Propensity to migrate vs. actual migrations across years



Notes: This figure depicts the proportion of Israeli migrants over time as well the predicted average propensity to migrate, as derived from our machine learning model.

Figure A6: Pre-event trends in a panel event study following Freyaldenhoven et al. (2019)



Notes: An unobserved factor potentially causes endogeneity, manifested as a pre-trend in the acquisition outcome. The log of the number of investors is likely to be affected by the confound, but, as we show in Table 5, not by the migration event. Applying the approach by Freyaldenhoven et al. (2019), we use this covariate to learn the dynamics of the confound and adjust for it in a 2SLS model. In Panel A, we depict regression coefficients on indicators for time relative to migration for both the likelihood of being acquired and the log of the number of investors as outcomes in a regression including startup, age, and age of migration fixed-effects. We scale the coefficients by dividing by their standard deviation in the pre-period. Panel B reports the coefficients of a 2SLS model using the forward lag of the treatment to instrument for the log of the number of investors. This model includes the same fixed effects as in Panel A.

Table A1: Panel A. Summary statistics for startups founded between 1990 and 2002

	Did Not Migrate to US		Migrated to US	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Num. Prior Successful Startups	0.217	(0.713)	0.515	(1.304)
Num. Founders	1.877	(1.017)	2.495	(1.091)
University T.T.O. Investment (0/1)	0.00850	(0.0919)	0	(0)
University Spinoff (0/1)	0.142	(0.350)	0.0707	(0.258)
Has Finding from Israeli Chief Scientist (0/1)	0.211	(0.409)	0.101	(0.303)
Initial Trademarks	0.0893	(0.300)	0.131	(0.395)
Initial Number of Patents	0.275	(0.629)	0.444	(0.848)
Financing in First Round (mill. $)	1.670	(3.088)	3.592	(4.553)
Final Num. Investors	4.335	(4.310)	6.889	(4.544)
Final Num. US Investors	0.714	(1.481)	2.566	(2.673)
Final Num. US VCs	0.312	(0.911)	1.596	(1.678)
Final Num. Non-US Investors	3.621	(3.510)	4.323	(2.931)
First Round Has US VC	0.0531	(0.224)	0.253	(0.437)
Clean Tech (0/1)	0.0871	(0.282)	0.0101	(0.101)
Communication Technology (0/1)	0.191	(0.394)	0.212	(0.411)
IT / Software (0/1)	0.218	(0.413)	0.455	(0.500)
Internet (0/1)	0.0563	(0.231)	0.131	(0.339)
Life Sciences (0/1)	0.128	(0.334)	0.0404	(0.198)
Medical Devices (0/1)	0.132	(0.338)	0.0606	(0.240)
Miscellaneous (0/1)	0.134	(0.341)	0	(0)
Semiconductor (0/1)	0.0542	(0.227)	0.0909	(0.289)
Haifa (0/1)	0.0935	(0.291)	0.0707	(0.258)
North (0/1)	0.105	(0.307)	0.0202	(0.141)
Center (0/1)	0.365	(0.482)	0.263	(0.442)
West Bank (0/1)	0.0117	(0.108)	0	(0)
Jerusalem (0/1)	0.0765	(0.266)	0.0505	(0.220)
Tel Aviv (0/1)	0.298	(0.457)	0.586	(0.495)
Initial Num. US Inventors	0.165	(1.394)	0.818	(2.042)
Initial Num, Israeli Inventors	1.055	(3.816)	1.929	(4.669)
Founder is University Professor	0.113	(0.316)	0.0707	(0.258)
Has Funding from Israeli Chief Scientist (0/1)	0.370	(0.483)	0.182	(0.388)
First Round Num. of VC Investors	0.413	(0.833)	1.040	(1.237)
First Round Num. of Corp. VC Investors	0.0329	(0.179)	0.0606	(0.279)
First Round Num. of Angel Group Investors	0.0149	(0.130)	0.0707	(0.258)
First Round Num. of Insurance Company Investors	0.00213	(0.0461)	0	(0)
First Round Num. Private Equity Investors	0.0276	(0.164)	0.0606	(0.279)
First Round Bank Num. Holding Investors	0.00106	(0.0326)	0	(0)
First Round Num. US Investors	0.177	(0.517)	0.455	(0.812)
First Round Num. US VCs	0.0691	(0.349)	0.343	(0.657)
First Round Num. Non-Israeli Investors	0.299	(0.669)	0.717	(1.134)
First Round Num. Israeli Investors	0.967	(0.966)	0.970	(1.138)
First Round Num. Non-Israeli VC	0.0903	(0.388)	0.424	(0.771)
First Round Num. Israeli VC	0.323	(0.676)	0.616	(0.866)
Founding Year	1998.2	(2.852)	1998.9	(2.162)
Total Amount Raised (mill. $)	10.73	(20.11)	32.48	(35.79)
Total Amount Raised Led by US VC (mill $)	3.294	(12.69)	20.33	(30.15)
Exit (Acquisition) Value	63.67	(107.5)	102.3	(112.4)
Acquired (0/1)	0.257	(0.437)	0.606	(0.491)
Acquired Outside US (0/1)	0.111	(0.314)	0.0404	(0.198)
IPO (0/1)	0.0712	(0.257)	0.0808	(0.274)
US IPO	0.0276	(0.164)	0.0707	(0.258)
Israel IPO (in Tel-Aviv Exchange)	0.0276	(0.164)	0	(0)
Applies for a Trademark (0/1)	0.310	(0.463)	0.687	(0.466)
Final Num. of Patents	3.188	(13.91)	4.808	(8.532)
Observations	1040			

Table A1: Panel B. Summary statistics for startups founded between 2003 and 2014

	Did Not Migrate to US		Migrated to US	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Num. Prior Successful Startups	0.272	(0.724)	0.800	(1.533)
Num. Founders	2.039	(1.068)	2.600	(1.375)
University T.T.O. Investment (0/1)	0.00658	(0.0809)	0	(0)
University Spinoff (0/1)	0.102	(0.302)	0.107	(0.311)
Has Finding from Israeli Chief Scientist (0/1)	0.0959	(0.295)	0.0800	(0.273)
Initial Trademarks	0.0714	(0.258)	0.280	(0.559)
Initial Number of Patents	0.183	(0.532)	0.360	(0.782)
Financing in First Round (mill. $)	0.964	(3.768)	3.752	(5.191)
Final Num. Investors	2.497	(2.337)	5.547	(3.670)
Final Num. US Investors	0.297	(0.793)	2.253	(2.320)
Final Num. US VCs	0.147	(0.503)	1.667	(1.803)
Final Num. Non-US Investors	2.200	(1.982)	3.293	(2.774)
First Round Has US VC	0.0461	(0.210)	0.427	(0.498)
Clean Tech (0/1)	0.0808	(0.273)	0	(0)
Communication Technology (0/1)	0.134	(0.341)	0.160	(0.369)
IT / Software (0/1)	0.183	(0.387)	0.293	(0.458)
Internet (0/1)	0.238	(0.426)	0.347	(0.479)
Life Sciences (0/1)	0.123	(0.329)	0.120	(0.327)
Medical Devices (0/1)	0.135	(0.342)	0.0267	(0.162)
Miscellaneous (0/1)	0.0667	(0.250)	0.0133	(0.115)
Semiconductor (0/1)	0.0385	(0.193)	0.0400	(0.197)
Haifa (0/1)	0.0921	(0.289)	0.0267	(0.162)
North (0/1)	0.0949	(0.293)	0	(0)
Center (0/1)	0.312	(0.464)	0.253	(0.438)
West Bank (0/1)	0.00282	(0.0530)	0	(0)
Jerusalem (0/1)	0.0583	(0.234)	0.0533	(0.226)
Tel Aviv (0/1)	0.396	(0.489)	0.667	(0.475)
Initial Num. US Inventors	0.0733	(0.775)	1.240	(3.140)
Initial Num, Israeli Inventors	0.966	(6.011)	1.053	(2.686)
Founder is University Professor	0.0874	(0.283)	0.0933	(0.293)
Has Funding from Israeli Chief Scientist (0/1)	0.163	(0.369)	0.107	(0.311)
First Round Num. of VC Investors	0.232	(0.593)	0.947	(1.025)
First Round Num. of Corp. VC Investors	0.00846	(0.0916)	0	(0)
First Round Num. of Angel Group Investors	0.0282	(0.171)	0.0533	(0.226)
First Round Num. of Insurance Company Investors	0.000940	(0.0307)	0	(0)
First Round Num. Private Equity Investors	0.00752	(0.0864)	0.0133	(0.115)
First Round Bank Num. Holding Investors	0.000940	(0.0307)	0	(0)
First Round Num. US Investors	0.105	(0.363)	0.640	(0.765)
First Round Num. US VCs	0.0526	(0.251)	0.573	(0.756)
First Round Num. Non-Israeli Investors	0.164	(0.483)	0.693	(0.788)
First Round Num. Israeli Investors	0.604	(0.754)	0.480	(0.760)
First Round Num. Non-Israeli VC	0.0733	(0.304)	0.587	(0.773)
First Round Num. Israeli VC	0.159	(0.463)	0.360	(0.690)
Founding Year	2006.6	(2.585)	2006.0	(2.118)
Total Amount Raised (mill. $)	3.933	(11.46)	30.15	(37.75)
Total Amount Raised Led by US VC (mill $)	1.273	(7.918)	21.49	(33.84)
Exit (Acquisition) Value	60.66	(119.5)	175.6	(216.0)
Acquired (0/1)	0.137	(0.344)	0.613	(0.490)
Acquired Outside US (0/1)	0.0508	(0.220)	0.0533	(0.226)
IPO (0/1)	0.0310	(0.173)	0.0667	(0.251)
US IPO	0.00940	(0.0965)	0.0267	(0.162)
Israel IPO (in Tel-Aviv Exchange)	0.0169	(0.129)	0.0133	(0.115)
Applies for a Trademark (0/1)	0.124	(0.330)	0.413	(0.496)
Final Num. of Patents	2.117	(27.39)	3.560	(10.65)
Observations	1139			

Table A2: Top 50 most relevant startup features in our random forest model

Order	Feature Name	Mean Importance	Std. Dev.
1	Invested by: Hutchison Kinrot	.03	.063
2	Share US Inventors in Patents	.024	.058
3	Invested by: VLVJ	.022	.053
4	Invested by: TechLoft	.02	.057
5	Invested by: Mediseed	.02	.055
6	Invested by: DreamIt Ventures Israel	.018	.05
7	Invested by: Trendlines	.018	.054
8	Invested by: Storm Ventures LLC	.018	.054
9	Invested by: Platonix Technologies	.018	.052
10	Share of US Inventors X Pension Fund Investment	.018	.054
11	Log(Amount Raised First Round+1) X Share US Inventors	.017	.051
12	Invested by: 3Com Ventures	.017	.048
13	Invested by: Stata Venture Partners*	.017	.05
14	Invested by: Garage Technology Ventures LLC	.015	.044
15	Invested by: Hummer Winblad Venture Partners	.015	.05
16	Invested by: Yozmot HaEmek Ltd. (formerly Ofek La	.015	.051
17	Invested by: BOS - Better On-line Solutions Ltd.	.014	.051
18	Invested by: Technology Partners LLC	.014	.041
19	Invested by: Synergy Venture Partners LP	.014	.042
20	Invested by: Marvell Technology Group	.014	.052
21	Invested by: Equity Group Investments	.014	.044
22	Invested by: Ridgewood Capital	.013	.045
23	Invested by: Western Technology Investments (WTI)	.013	.047
24	Invested by: Institutional	.012	.043
25	Invested by: Innovacom	.012	.04
26	Invested by: Biznovate	.012	.043
27	Invested by: Avnan Investments LP	.012	.044
28	Invested by: WELP	.012	.042
29	Invested by: Integral Capital Partners	.012	.044
30	Invested by: WNIC	.012	.044
31	Invested by: LN	.011	.038
32	Log(Amount Raised in First Round +1)	.011	.04
33	Invested by: Rotem Ventures	.011	.041
34	Invested by: Dead Sea Works	.011	.041
35	Invested by: The Junction	.011	.049
36	Invested by: CenterPoint Venture Partners	.011	.038
37	Invested by: The Library	.011	.037
38	Invested by: Jerusalem Global (Investment Bank)	.01	.035
39	Invested by: Yissum	.01	.038
40	Invested by: DCM	.01	.04
41	Invested by: Rho Ventures	.0099	.039
42	Invested by: Meytag	.0096	.033
43	Invested by: Flanders Language Valley (FLV) Fund C	.0094	.043
44	Invested by: Technology Incubator Arad	.0093	.038
45	Invested by: ATI	.0092	.038
46	Invested by: Alta Berkeley Venture Partners	.0091	.037
47	Invested by: Challenge I	.009	.034
48	Invested by: Band of Angels	.0089	.039
49	Invested by: Trendlines Israel Fund	.0087	.031
50	Invested by: Calanit Carmon	.0087	.035

Notes: In this table, we report the results from 50 random forest models estimated with a (random) 60% subsample of the data. The dependent variable in these models is an indicator for whether an Israeli startup migrates to the US. *Feature importance* is defined as the change in the total predictive power between a random forest that includes the feature and one that does not (Breiman, 2001). *Std. Dev.* is the standard deviation of the 50 estimates of a given feature's importance.

Table A3: List of subsectors

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 A4: Balance analysis of startup characteristics for the region of common support in the quasi-experimental sample

Variable	(1) Non-Migrants (Control)	(2) Migrants (Treated)	(3) Difference
University T.T.O. Investment (0/1)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
University Spinoff (0/1)	0.167	0.095	-0.071
	(0.377)	(0.295)	(0.061)
Has Funding from Israeli Chief Scientist (0/1)	0.143	0.131	-0.012
	(0.354)	(0.339)	(0.065)
Has Initial Patents	0.071	0.143	0.071
	(0.261)	(0.352)	(0.061)
Has Initial Trademarks	0.048	0.131	0.083
	(0.216)	(0.339)	(0.057)
First Round Has US VC	0.000	0.012	0.012
	(0.000)	(0.109)	(0.017)
Observations	42	84	126

Table A5: Performance of stayers, distinguishing between restricted and non-restricted subsectors

	(1) Ln(VC +1)	(2) Acquired	(3) Acquired Outside US	(4) IPO	(5) Exit	(6) Ceased to Operate
Restricted Subsector	0.589***	0.0237	0.0121	0.0813	0.105	-0.173**
	(0.145)	(0.0535)	(0.0444)	(0.0518)	(0.0782)	(0.0691)

Notes: This table compares the performance of quasi-exogenous stayers with that of non-exogenous stayers. The latter operate in the same sectors as the quasi-exogenous stayers, but belong to non-restricted subsectors. Only those firms in the region of common support of the quasi-experiment are included. Founding year and sector fixed effects are used. Standard errors are clustered at the founding year level. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table A6: The effect of migrating to the US on Israeli startups' performance outcomes: With subsector fixed effects in the LASSO variable selection

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC +1)	(4) Ln(VC +1) (US VC Led Only)	(5) Acquired	(6) Acquired by non-US firm	(7) IPO
Double-LASSO							
Moves to US	0.267***	0.0903	1.167***	1.127***	0.209**	-0.0767*	0.0248
	(0.0542)	(0.0758)	(0.0858)	(0.0819)	(0.0638)	(0.0354)	(0.0332)
R^2	0.242	0.493	0.442	0.389	0.275	0.112	0.169

Notes: This table reports the estimates for the impact of migrating on startup performance estimating a double-LASSO model that includes subsector fixed effects in the variable selection process of both the selection and treatment equations. We control for subsector and founding year fixed effects. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table A7: Coarsened exact matching cross-sectional estimates

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC +1)	(4) Ln(VC +1) (US VC Led Only)	(5) Acquired	(6) Acquired by non-US firm	(7) IPO
Moves to US	0.277**	0.428**	0.673***	0.695**	0.255***	-0.0541	0.0545
	(0.101)	(0.145)	(0.124)	(0.264)	(0.0501)	(0.0463)	(0.0502)
Observations	213	213	213	213	213	213	213
R^2	0.725	0.738	0.789	0.672	0.633	0.560	0.678

Notes: We implement a coarsened exact matching algorithm and construct a sample that matches migrants on sector, founding year, amount of US VC raised in the first round, total amount raised, and whether a startup applied for a US granted patent at founding or the year after. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A8: The effect of migrating to the US on Israeli startups' yearly financing outcomes

	(1) Log (VC+1)	(2) Log (US VC+1)	(3) Log (VC+1) Incl. Late Movers	(4) Log (US VC+1) Incl. Late Movers
Model I: Main Difference				
Has Moved	0.133	0.267^{***}		
	(0.115)	(0.0752)		
Has Moved			0.235^{**}	0.229^{***}
			(0.104)	(0.0573)
R^2	0.245	0.357	0.247	0.357

Notes: This table reports the estimates for the impact of migrating on a startup's yearly amount of financing raised, exploiting within migrant variation. *Has Moved* is an indicator that takes on value 1 starting from the year in which a startup established its headquarters in the US and zero in the pre-migration period. The results in columns (1) and (2) are for the same sample as in Table 4. The results in columns (3) and (4) are for a sample including startups that migrated after their third year of age. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A9: Robustness test to assess the influence of unobservables on the startups' intermediate performance outcomes: Oster (2019) bounding method.

	(1) Applied for Trademark	(2) Ln(VC +1)	(3) Ln(VC +1) (US VC Led Only)
Model I: Baseline (N=2179)			
Moves to US	0.348^{***}	1.610^{***}	1.571^{***}
	(0.0297)	(0.0505)	(0.0211)
Model II: Double-LASSO (N=2179)			
Moves to US	0.256^{***}	1.112^{***}	1.096^{***}
	(0.0581)	(0.107)	(0.128)
R2 Baseline	0.153	0.214	0.192
R2 LASSO	0.264	0.463	0.406
R2 Max	0.375	0.657	0.576
β^* (lower bound)	0.165	0.722	0.718
δ	2.794	2.851	2.897

Notes: In this table, we implement the Oster (2019) bounding method to compute a lower bound for the migration effects on our intermediate outcomes. We derive the relationship between R_{max}–that is, the R-squared from a hypothetical regression of the outcome on the treatment and both observed and unobserved controls–and $\tilde{R}$–that is, the R-squared from the controlled regression–from our machine learning model. To estimate the coefficient of proportionality, π, we consider that: i) if the outcome can be fully explained by the treatment and full controls set, R_{max} is equal to 1; and ii) our controlled model explains approximately 70% of the selection into migration; therefore iii) the coefficient of proportionality between R_{max} and $\tilde{R}$ we use is computed as $\pi = 1/0.7 = 1.43$. In each column, the baseline specification controls for founding year and sector fixed effects, while the expanded specification includes all the double-LASSO controls. As shown, the lower bounds (β) of our estimates are all above zero. Moreover, the reported measure, δ, for the relative degree of selection on observed and unobserved variables suggests that the influence of the unobservables relative to the observables would need to be over 2.8 times larger to produce a null migration effect. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance noted as: *p <0.10; **p <0.05; ***p <0.01.

Table A10: Hazard of exiting successfully

	(1) Exit	(2) Acquired	(3) IPO
Moves to US	3.197***	5.943***	0.819
	(0.981)	(2.553)	(0.493)
N	126	126	126
Log-Likelihood	-288.7	-206.6	-65.28

Notes: We estimate Cox proportional hazard models on cross-sectional data using the quasi-experimental sample described in Section 4 (Model III). Standard errors (in parentheses) are clustered at the founding year level. We do not estimate the double-LASSO model given that our maximum likelihood estimator would not converge with the inclusion of the several covariates we selected. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A11: The effect of migrating to the US on the Israeli startups' likelihood of exiting via an IPO, differentiating by Stock Exchange

	(1) IPO	(2) US IPO	(3) Israel (TASE) IPO
Model II: Double-LASSO			
Moves to US	0.0357	0.0230	-0.0161
	(0.0410)	(0.0216)	(0.0145)
Model III: Quasi-Experiment			
Moves to US	0.0111	0.0403	-0.0828
	(0.0875)	(0.0490)	(0.0613)

Notes: This table reports the estimates of the effect of migrating to the US on the likelihood of exiting via an IPO. We distinguish between those IPOs that took place on the US stock exchanges (NASDAQ and NYSE) and those that occurred on the Tel Aviv stock exchange (TASE). Model II includes founding year and subsector fixed effects, and Model III only founding year fixed effects. Standard errors (in parentheses) are double-clustered at founding year and sector levels in Model II, and bootstrapped in Model III. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A12: The effect of migrating to the US on Israeli startups' survival: cross-sectional results

	(1) Ceased to Operate
Model I: Naive (N=2179)	
Moves to US	-0.465***
	(0.0253)
Model II: Double-LASSO (N=2179)	
Moves to US	-0.219***
	(0.0607)
Model III: Quasi-Experiment (N=126)	
Moves to US	-0.288***
	(0.105)

Notes: This table reports the likelihood that a company ceases to operate. The *Ceased to Operate* outcome indicator identifies startups that either went bankrupt according to IVC, or did not receive any financing for a period of five consecutive years. Model I is the naive model described in the text. Model II is the double-LASSO model. Model III is our quasi-experiment exploiting exogenous institutional constraints on the startups' ability to migrate. Model II includes founding year and subsector fixed effects, while Model III only founding year fixed effects . Standard errors (in parentheses) are double-clustered at founding year and sector levels for Model II and bootstrapped for Model III. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table A13: Robustness test to assess the influence of unobservables on the startups' equity outcomes: Oster (2019) bounding method

	(1) Acquired	(2) Acquired by US firm	(3) Ln(Exit $)
Model I: Baseline (N=2179)			
Moves to US	0.412***	0.448***	1.259***
	(0.0390)	(0.0291)	(0.199)
Model II: Double-LASSO (N=2179)			
Moves to US	0.174**	0.247***	0.996***
	(0.0733)	(0.0564)	(0.240)
R2 Baseline	0.109	0.134	0.129
R2 LASSO	0.303	0.316	0.368
R2 Max	0.430	0.449	0.522
β^* (lower bound)	0.0174	0.101	0.826
δ	1.112	1.687	5.851

Notes: In this table, we implement the Oster (2019) bounding method to compute a lower bound for the migration effects on our startup equity outcomes. As shown, the lower bounds of our migration effects (β) are all above zero. Moreover, the reported δ for these equity outcomes suggests that the influence of unobservables relative to observables would need to be over 1.1 times larger to produce a null migration effect. Significance noted as: *p <0.10; **p <0.05; ***p <0.01.

Table A14: The effect of migrating to the US on Israeli startups' equity outcomes controlling for intermediate performance outcomes

	(1) Acquired	(2) Acquired by US firm	(3) IPO
Model II: Double-LASSO (N=2179)			
Moves to US	0.143*	0.223***	0.0142
	(0.0730)	(0.0532)	(0.0414)
Ln(VC Raised in US +1)	0.0311**	0.0235*	0.0168
	(0.0130)	(0.0105)	(0.00955)
Ln(Patents +1)	0.0946***	0.0724***	0.0351**
	(0.0154)	(0.0162)	(0.0135)
Has Trademark	0.0124	-0.0149	-0.00185
	(0.0379)	(0.0415)	(0.0251)

Notes: This table reports the effects of migrating on the startups' equity outcomes controlling for intermediate performance measures such as VC fundraising, patenting, and trademarks in the double-LASSO model. We include founding year and subsector fixed effects. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.10, ** p <0.05, *** p <0.01.

Table A15: Instrumental variables results on equity outcomes

	(1) Acquired	(2) Acquired by non-US Firm	(3) IPO	(4) Exit
Has Moved	0.0528**	0.0161*	-0.00721	0.0456**
	(0.0248)	(0.00891)	(0.0154)	(0.0219)
Observations	1869	1869	1869	1869
Underidentification Test	5.187	5.187	5.187	5.187

Notes: This table reports the 2SLS estimates for the impact of migrating on startup equity outcomes, exploiting within-migrant variation. We include fixed effects for each startup, startup age, and age at migration. We also control for time-varying differences in a startup's initial traction using the total number of investors that have invested in a startup over time. We instrument this variable with the first lead of the *Has Moved* indicator as recommended by Freyaldenhoven *et al.* (2019). StanDard errors (in parentheses) are clustered by founding year. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A16: Headquarter migration versus the opening of a branch

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC +1)	(4) Ln(VC+1) (US VC-Led Only)	(5) Acquired	(6) Acquired by non-US Firms	(7) Ln(Exit $)	(8) IPO
Moves to US	0.282***	0.101	1.199***	1.175***	0.181**	-0.0689*	0.905**	0.0426
	(0.0649)	(0.154)	(0.125)	(0.111)	(0.0683)	(0.0358)	(0.280)	(0.0397)
Opens Subsidiary in US	0.211*	0.242	0.731***	0.582***	0.0566	-0.00465	0.0288	0.116**
	(0.106)	(0.147)	(0.205)	(0.165)	(0.0662)	(0.0477)	(0.373)	(0.0458)
N	2171	2171	2171	2179	2171	2171	364	2171
R^2	0.273	0.319	0.473	0.390	0.303	0.133	0.297	0.184

Notes: This table compares the performance of each migrant type, namely the startup establishing its headquarters in the US and the one opening a branch, to that of non-migrants. We present the results from the double-LASSO models. We examine the same startup performance outcomes as those investigated in Table 3 and Table 6. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.

Table A17: The effect of migrating, by US state destination

	(1) Applied for Trademark	(2) Ln(Patents+1)	(3) Ln(VC +1)	(4) Ln(VC +1) (US VC Led Only)	(5) Acquired	(6) Acquired by non-US firm	(7) Ln(Exit $)	(8) IPO
Moves to California	0.238**	0.0667	1.213***	1.458***	0.183	-0.0531	1.038**	0.00651
	(0.0776)	(0.129)	(0.259)	(0.247)	(0.135)	(0.0407)	(0.327)	(0.0370)
Moves to Massachusetts	0.234	0.200	1.173***	0.816*	0.160	-0.103*	1.315*	0.0481
	(0.129)	(0.267)	(0.323)	(0.400)	(0.0975)	(0.0517)	(0.623)	(0.0694)
Moves to New York area	0.315***	0.0974	1.094***	0.946**	0.140	-0.0733	1.161	0.0952
	(0.0445)	(0.125)	(0.224)	(0.398)	(0.104)	(0.0507)	(0.693)	(0.0739)
Moves to other US state	0.231*	-0.255	0.591	0.141	0.232	-0.0868	-0.207	0.0122
	(0.114)	(0.143)	(0.392)	(0.326)	(0.154)	(0.0686)	(0.440)	(0.0977)
Observations	2171	2171	2171	2171	2171	2171	364	2171
R^2	0.264	0.508	0.464	0.417	0.303	0.141	0.381	0.215

Notes: This table examines whether there are any differences in migration benefits depending on the US location Israeli startups choose. We differentiate between the California, Massachusetts, and New York area (including New Jersey) destination locations, on the one hand, and the remaining US locations, on the other. We examine the same startup performance outcomes as those investigated in Table 3 and Table 6. Standard errors (in parentheses) are double-clustered at founding year and sector levels. Significance denoted as: * p <0.1, ** p <0.05, *** p <0.01.