The Startup Performance Disadvantage(s) in Europe: Evidence from Startups Migrating to the U.S.*

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Abstract

This paper uses novel data on the migration of European startups to the United States to understand Europe's main disadvantages in startup performance. I use positive sorting in migration as an identification strategy: because of positive sorting, the simple cross-sectional comparison gives an upper bound on the effect of the U.S. ecosystem compared to the European one. Results show that U.S. migrants receive much more venture capital (VC) funding, produce more innovation, and reach much bigger scale by exit than startups staying in Europe. More surprisingly, however, U.S. migrants do not increase revenue for many years after migration, incur higher losses for long time periods, and do not have a higher likelihood of successful exit than European stayers. Furthermore, a large part of the difference in innovation and scale can be explained by the U.S. funding advantage. The results suggest that Europe's funding market, rather than its product or exit markets, is the primary obstacle to startup performance.

Keywords: Entrepreneurship, Entrepreneurial Ecosystem, Migration, Startup Performance

JEL: F21, F22, L26, M13

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Abstract

This paper uses novel data on the migration of European startups to the United States to understand Europe's main disadvantages in startup performance. I use positive sorting in migration as an identification strategy: because of positive sorting, the simple cross-sectional comparison gives an upper bound on the effect of the U.S. ecosystem compared to the European one. Results show that U.S. migrants receive much more venture capital (VC) funding, produce more innovation, and reach much bigger scale by exit than startups staying in Europe. More surprisingly, however, U.S. migrants do not increase revenue for many years after migration, incur higher losses for long time periods, and do not have a higher likelihood of successful exit than European stayers. Furthermore, a large part of the difference in innovation and scale can be explained by the U.S. funding advantage. The results suggest that Europe's funding market, rather than its product or exit markets, is the primary obstacle to startup performance.

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"There is no Silicon Valley and no Big Tech companies here [in Europe]. What do you think is the reason for that?"

"That is the one-trillion-dollar question."

— Peter Thiel; entrepreneur, in response to newspaper interviewer

1 Introduction

The rapid growth of venture capital-backed startups into global technology companies is one of the defining economic trends of our time, and Europe is largely missing out. For example, eight out of the ten most valuable companies in the world are all young, innovative technology companies ("technology giants") that financed their early growth with venture capital, and none of them is from Europe (all eight are from the U.S.).[1] Europe is also far behind when it comes to the next generation of companies that may rise to these ranks - the so-called unicorns, i.e., startups with a valuation of greater than 1 billion USD: 51% of all unicorns existing in 2021 are from the U.S. and 13% from Europe, while both regions are of similar size in terms of GDP.[2][3]

There has been a great deal of speculation as to what are the reasons behind Europe's lower startup performance. Common hypotheses include: a lack of (experienced) venture capital (Bertoni et al., 2011; Puri and Zarutskie, 2012; Axelson and Martinovic, 2013), a lack of human capital, in particular entrepreneurs (Audretsch and Keilbach, 2004) and inventors (Chen et al., 2021), lacking technology (Marshall, 1890; Romer, 1990; Arora et al., 2001), as well as a host of other hypotheses such as, among others: the fragmented product market, inadequate markets for startup initial public offerings (IPOs) or acquisitions (Black and Gilson, 1998; Jeng and Wells, 2000), rigid labor laws, regulation, and risk aversion. However, there is little systematic evidence on which of these factors explain the startup disadvantage, let alone their relative importance.

In this paper, I take one step to understand the European startup performance disad-

[1] As of March 15, 2023, these companies are: Apple, Microsoft, Alphabet, Amazon, Tesla, Meta, NVIDIA, and Visa (see https://www.companiesmarketcap.com/).

[2] According to https://www.cbinsights.com/, there are 984 unicorns worldwide as of December 2021, of which 500 are from the U.S., 301 from Asia, and 130 from Europe.

[3] In this paper, I use "Europe" to refer to the geographical continent of Europe as defined in the United Nations Statistics Division's M49 standard, i.e., 51 countries (see https://unstats.un.org/unsd/methodology/m49/, accessed on February 7, 2022). The GDP in Europe and the U.S. was 22.9tn USD and 20.9tn USD in 2020, respectively (see https://data.worldbank.org/indicator/NY.GDP.MKTP.CD, accessed on February 7, 2022).

vantage by analyzing European startups migrating to the U.S. The idea is to observe how startups who move their headquarters to the U.S. (which I call "migrants") perform after migration - compared to startups staying in Europe - in various performance areas, e.g., fundraising, innovation, revenue, profitability, and exit success - to understand where Europe's biggest disadvantages are. Results show that U.S. migrants raise much more funding, produce more innovation, and reach much bigger scale by exit than startups staying in Europe. Surprisingly, however, U.S. migrants do not increase revenue for many years after migration, but instead incur higher losses for longer time periods, and do not have a higher likelihood of successful exit than European stayers. Moreover, main parts of the innovation and scale advantage can be explained by the U.S. funding advantage. I conclude that financing is likely the biggest obstacle to European startup growth, while markets for technology, products, and exits do not seem to hinder European startups very much, if at all.

The approach of this paper poses two main challenges. First, data on startup migration is not readily available. I overcome the data challenge by hand-collecting a novel data set on the headquarter location history of approximately 11,000 European startups. The data set is based on an industry-standard data set of VC-backed European startups first financed between 2000 and 2014 (to allow time to observe performance until 2021) from VentureSource. Then, I collected a timed history of headquarter locations using (historical) web footprints and national business registration records. Finally, I merged the data with several other data sets, such as Orbis, Preqin, SDC New Issues, SDC M&A, and PATSTAT, to acquire performance measures in various areas such as: innovation, commercial success, and exits.

Second, the decision to emigrate is determined by the startup owners, making it an endogenous choice. To overcome this endogeneity challenge, I use a combination of theory and empirical observation. Theoretically, as migration comes with a cost, we should expect those startups to migrate which gain the most from moving to the world-leading startup ecosystem in the U.S. If those with the largest expected gains move, the performance difference between migrants and stayers will give an upper bound on the advantage treatment effect of the U.S. startup ecosystem compared to the European one. As a consequence, if we compare performance measures in different areas, and we do not find a difference in some of them,

we can be quite confident that Europe does not hinder startups in these areas.

I begin the empirical analysis by showing that a positive selection of startups migrates to the U.S. I find that startup migrants, on average, are younger, have raised more financing, are backed by more (U.S.) investors, and have more patents at the first funding round, than European stayers. This observed positive selection is important, as it confirms the upper-bound argument. Additionally, U.S. migration tends to happen early in the startup life cycle: the average migrant moves 1 year after first funding, and 76% of migrants have moved by year 3 after first funding. By moving early, U.S. migrants spend a significant amount of time in their new environment, allowing for performances to be affected over long event windows.

Moving on to analyzing post-migration performance, the first set of findings is not surprising. I find that U.S. migrants raise much more venture capital (VC) funding, and innovate more, in terms of number of patents and citation-weighted patents, than European stayers. This is consistent with the idea that the U.S. startup ecosystem is a world leader in providing venture capital and developing novel technologies. However, it should be noted that the differences in fundraising and innovation may not be necessarily the result of the difference in the ecosystems, but could be simply caused by the positive selection of startups migrating to the U.S.

More importantly, and surprisingly, I find that startups migrating to the U.S. do not experience an increase in revenue and instead accumulate substantially more net losses in the years subsequent to their migration. From anywhere between 1 and 8 years after migration, migrants do not see any rise in revenues but, instead, experience significantly higher net losses than those startups that remain in Europe. Furthermore, U.S. migrants are not any more likely than European stayers to achieve a successful exit in the form of an initial public offering (IPO) or acquisition at a valuation of more than two times the amount of capital raised. This is contrary to what we would expect if the large U.S. markets for customers, acquirers, and IPOs were significant sources of the competitive advantage of the U.S. startup ecosystem compared to its European counterpart.

These previous findings are somewhat contradictory: Startups moving U.S. receive much more funding and produce more innovation, but they do not increase revenues or exit proba-

bilities. Instead, U.S. migrants sustain long periods of financial losses, compared to European stayers. To understand this apparent contradiction I also look at another performance area: the scale that startups have at the moment of exit. I find that U.S. migrants, at the moment of an (equally likely) exit, are worth many times more, have more employees, more revenue, and are older than startups that exit in Europe. At the same time, they still have higher net losses at the moment of exit.

Thus, the analysis reveals a key difference between the U.S. and European ecosystems: a focus on achieving greater company scale, facilitated by a higher tolerance to financial losses and more venture capital funding. That is, long-term firm scale, as opposed to short-term sales, profit, or exit success seems to be an important criterion for U.S.-based firms to achieve after getting VC financed. The U.S. financing advantage plays a critical role in enabling this focus - without financing, the extended periods of losses to grow would not be sustainable. Consistent with the argument that financing is the key difference between the ecosystems, I find that the financing advantage can explain a large part of the performance difference in the areas of innovation and scale at exit. In other words, startups staying in Europe that have received comparable funding to U.S. migrants are much more comparable to U.S. migrants in terms of innovation output and scale at exit.

Overall, my findings show that European startups moving to the U.S. mainly benefit from larger funding amounts, and a greater tolerance to financial losses, which allow reaching a larger firm scale before going public or being acquired. The finding that European stayers develop their revenues and successful exit frequencies at least as well as U.S. migrants indicates that local product and exit markets hinder European startups little, if at all.

My empirical results contrast with the small prior literature on the impact of startup migration on performance. Guzman (2019) examines U.S. startups migrating to the Silicon Valley between 1996 and 2005 and finds that moving benefits startups across the board, leading to increased financing, acquisitions or IPOs, patents, product launches, and sales growth. Moreover, the financial benefits disappear after 2001, while the non-financial benefits persist. Similarly, Conti and Guzman (2021) examine Israeli startups founded 1990 and 2014 and find benefits for U.S. movers in various performance dimensions, including larger funding amounts, trademark acquisition, and higher chances of being acquired. The implication of

these studies is that the creation of a startup ecosystem requires comprehensive efforts on various fronts, including the markets for venture capital, IPOs, acquisitions, consumers, technology, and human capital. In contrast, my findings imply that improving European startup clusters is much more straightforward than previously thought: focus on improving venture capital markets.

What might explain these different findings? First, markets for IPOs, acquisitions, technology, and human capital may be globally accessible from Europe, minimizing the impact on European startup performance. Consistent with this argument, there is considerable evidence that markets for technology, products, IPOs, and M&As, are highly globalized today (Erel et al., 2012; Doidge et al., 2013; Audretsch et al., 2014; De Marco et al., 2017). Only the venture capital market persists to require local presence (Chen et al., 2010; Cumming and Dai, 2010; Lutz et al., 2013), explaining why European startups raise significantly more funding when relocating to the U.S. Second, European migrants may lack access to other benefits of the U.S. ecosystem besides venture capital financing, which is, albeit only partially, consistent with Michelacci and Silva (2007); Dahl and Sorenson (2012) who show that local entrepreneurs have better access to local resources.

This paper relates to a diverse set of prior literature. First, there is a large literature on the agglomerative clustering of entrepreneurship, starting with the seminal work of Saxenian (1994) and Glaeser et al. (2010), as well as Kerr and Robert-Nicoud (2020) who provide a more recent review. In this regard, my findings rhyme with recent evidence from Gornall and Strebulaev (2021) who underscore the causal role of the U.S. VC industry in today's U.S. tech dominance. Second, there is growing literature on the merits of entrepreneurship policies, such as Audretsch et al. (2007); Ferrary and Granovetter (2009); Lerner (2009); Hellmann and Thiele (2019). Many of these studies also underscore the importance of venture capitalists in the emergence of tech clusters, but often rely on anecdotal evidence or theoretical arguments. Finally, the results of this paper speak to the puzzle of the divergent productivity growth between Europe and the U.S. since 1995 (Van Ark et al., 2008). One explanation, put forward by Bloom et al. (2012), is that U.S. multinationals are better able to capitalize on the IT revolution. This paper indicates that the divergence in productivity may to some extent also be driven by the higher growth dynamics of U.S. startups, which

benefit from the more more developed U.S. VC industry.

2 Model of Selection into Migration

It is unlikely that the selection of firms that migrate to the U.S. is random, and I have no source of exogenous variation in migration to exploit in this paper. Here, I present a simple model to clarify the equilibrium relationship between migration and startup performance that we would expect if both can be determined endogenously. I use this simple consideration of which firms are likely to migrate to the U.S. to argue that cross-sectional data give a useful upper bound on the average causal effects of the U.S. startup ecosystem compared to the European one.

Let Π_i denote the performance of the startup i. The startup can choose to migrate to the U.S. or to remain in Europe, with the region choice being indexed by $R \in \{EU, US\}$. The U.S. ecosystem affects the performance of each startup individually by a certain factor, denoted as λ_i^{US}. Also, each startup faces a non-negative migration cost c_i. startup i can maximize its performance by migrating if $\left(1 + \lambda_i^{US} - c_i\right) \Pi_i > \Pi_i$, or if $\lambda_i^{US} > c_i$. That is, a startup will optimally migrate if the performance benefits of the U.S. ecosystem λ_i^{US} are higher than the cost c_i.

To assess the need for costly public interventions that improve local startup ecosystems, we are arguably most interested in estimating the quantity $\mathbb{E}_i\left[\lambda_i^{US} - c_i\right]$, that is, the average net effect the world-leading U.S. ecosystem has on startups compared to the local European ones. However, estimating this quantity requires that we have counterfactual startup performances if a startup stayed in Europe when it actually migrated to the U.S. Obviously, such counterfactual is not available.

If we used cross-sectional data instead to estimate the relative performance difference of startups moving to the U.S. and not moving, we would be measuring

$$\frac{\mathbb{E}_i\left[\left(1 + \lambda_i^{US} - c_i\right) \Pi_i | \lambda_i^{US} > c_i\right]}{\mathbb{E}_i\left[\Pi_i | \lambda_i^{US} < c_i\right]} - 1. \tag{1}$$

That is, we would observe performances of startups that optimally choose to migrate to the

U.S. relative to performances of startups that optimally choose to stay in Europe. Assume now that $\mathbb{E}_i[\Pi_i]$ is equal across the migrants and stayers. That is, the average performance of migrants, if they stayed in Europe instead, is equal to those startup that stay in Europe anyway. Then, the the observable cross-sectional difference of (1) becomes

$$\mathbb{E}_i\left[\left(\lambda_i^{US} - c_i\right)|\lambda_i^{US} > c_i\right] \geq \mathbb{E}_i\left[\lambda_i^{US} - c_i\right].$$

Thus, the difference between migrating and staying startups observable in the cross section would give us an *upper* bound on the average effect that the world-leading U.S. ecosystem has on European startups compared to the local ones.

However, contrary to the assumption made earlier, there are good reasons to believe that migrating startups are a positive selection. Reasons include that more capable startups may benefit more from greater resource agglomeration (Guzman (2019)) or be attracted to better pay for their (above-average) skills (Roy (1951); Borjas (1987)). If positive selection is the case (and some evidence is provided later in the paper), the simple cross-section between migrants and stayers gives an upward biased upper limit–and hence still an informative upper bound of the true effect of the U.S. ecosystem compared to the European one.

The intuition is simple. Startups that will benefit most from relocating to an advanced ecosystem are the most likely to do so. Thus, comparing the performance of those that migrate and those that remain gives an overestimation of the effect of the advanced ecosystem, giving us an upper bound on the average effect of the advanced ecosystem. It is important to note that there are many ways to measure startup performance, all of which emphasize different aspects. For instance, common measures of startup performance include fundraising, innovation, business success (sales and net income), exits, and exit valuation. If the cross-sectional comparison does not show a difference in some performance areas, it is safe to assume the U.S. ecosystem does not have an advantage over the European ecosystem in these same areas. Applying this logic, we can identify the areas where the European ecosystem does not hinder startup performance, and so identify its main weaknesses.

3 Data

This paper's analysis of U.S. migration of European startups and performance consequences makes use of several datasets. The data collection strategy is to take a representative data set of VC-funded startups and augment it with migration and performance data from various data sources. This section describes the data collection process and resulting sample.

3.1 Startups and Migration Data

I start with an industry-standard dataset of VC-funded startups from Dow Jones' VentureSource. VentureSource, along with Refinitiv's VentureXpert, are the two primary venture capital databases used in academic research (Da Rin et al. (2013)). We use VentureSource because with our filters it is more comprehensive than VentureXpert. To get a sample of VC-backed European startups, these filters are: 1) only financing rounds labeled "VC" (i.e., excluding buyout, angel, debt, grant, and exit financings), for which the financing date and amount are available; 2) the investee received its first VC between 2000 and 2014 and was no more than 10 years old at time of first VC; 3) the investee is from one of 17 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, and the United Kingdom. Using these filters, VentureSource lists 11.850 startups, which is about 30% more than the 8.961 obtained from VentureXpert (see Appendix Table A2).

Unlike VC funding data for startups, timed data on the headquarter locations of startups is not available in commercial datasets. Therefore, I manually collected the chronological history of each startup's headquarters as described in the following. First, I pulled all VC-backed startups from VentureSource that received their first VC investment between 2000 and 2014 and were funded from at least one European investor, regardless of the location of the startup's HQ.[4] Applying the above filters yields 14,588 startups, of which 10,917 are headquartered in Europe and 3,671 are headquartered outside of Europe, according to VentureSource. I let the sample start in 2000, because VentureSource has only provided

[4]I consider only financing rounds labeled as "VC", i.e., excluding buyout, angel, debt, grant, and exit financings; and only VC financings for which the date and financing amount are available.

comprehensive data on Europe since then (Axelson and Martinovic (2013); Retterath and Braun (2020)). Moreover, the upper bound of 2014 is chosen, because the dataset was assembled in July 2021 and so we give each startup at least 6.5 years to observe subsequent performance. This time span mirrors the choice in other venture capital analyses.[5]

Then, I manually researched HQ locations of each startup at the time of first VC and at end of the sample (i.e., the earliest of 2021, exit, or cease of operations). To identify each company's most recent HQ locations, I searched publicly available data sources such as the company's website, LinkedIn, and Crunchbase profiles. For historical HQ locations or if a webiste was defunct, we used the Internet Archive Wayback Machine and news articles from web searches.[6] The Internet Archive is a "digital library of Internet sites" which regularly stores billions of versions of public websites. Since these data are self-reported, we cross-checked HQ moves with official national trade registers. For example, if a company publicly announced a new HQ in the U.S., we verified this by checking publicly available U.S. business registration records. U.S. business registration regulations require companies to list at least two offices in a state: the office within the state and the principal executive office. Therefore, we only accepted a HQ migration if the web sources and business registration records indicated a move of HQ. When a HQ relocation was identified, I searched further to pinpoint the year it occurred. To do so, I searched Lexis/Nexis and the internet for news articles about the HQ move. If no news articles were found, I determined the year of the move by reviewing the Internet Archive to see when the HQ location was changed on the website.

Finally, the sample was restricted to all startups headquartered in one of these 17 European countries when they started: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, and the United Kingdom. These countries account for more than 98% of all VC financing rounds on the European continent in the database.

The data collection process above resulted in a final sample of 11,066 startups initially headquartered in Europe. Creating a balanced panel of 17 years after first funding, we get

[5](e.g., Hochberg et al. (2007); Nahata (2008); Ewens and Rhodes-Kropf (2015); Nanda et al. (2020) leave 4.5, 4, 6, and 8 years, respectively.)

[6]Website: `https://archive.org`, (last accessed July 22, 2021).

188,122 firm-year observations.

3.2 Startup Performance Data

I use a variety of measures of startup performance throughout the analysis, which may be categorized in five domains: fundraising, innovation, commercial success, exit likelihood, and scale at exit. These domains map into the ecosystem traits/benefits the U.S. may have to offer compared to the European one: better VC market, better innovation inputs, better product market, and better exit markets.

While VentureSource already provides comprehensive data on fundraising, it provides incomplete data on financials and exits, and no data on innovation performance at all. In this section, I describe the datasets merged to VentureSource to improve or add these latter information.

3.2.1 Obtaining Information on Financials

I supplement the financial and employment data of VentureSouce with data from two other commercial data providers: Preqin and Orbis. Preqin focuses on private capital markets collecting data at the investor, fund, and asset (i.e., company) level. Preqin collects its data from surveys, voluntary reporting, or involuntary reporting using Freedom of Information Act (FOIA) requests from institutional investors (or limited partners (LPs)) and private markets fund managers (or general partners (GPs))(Harris et al., 2014). On the other hand, Orbis provides harmonized financial data on more than 400 million firms from over 100 countries worldwide. The Orbis financial information comes directly from national business registers (Kalemli-Ozcan et al., 2015).

VentureSource is merged to the other databases by name and other identifying information with a procedure based on Bernstein et al. (2016) and described in detail in subsection A.1. The merge to Preqin and Orbis increases firm-year observations with financial information from about 9,000 in VentureSource only to over 41,000 firm-years (an over 300% increase). Table A3 tabulates the number of observations with financials over time starting from the year of first funding. We observe revenue and net income for about 28% of the

sample in the sixth year after first funding and at least one financial data point for about 62% of the sample.[7]

A disadvantage of Orbis in our context is that European coverage is better, because many national registries require annual financial reporting from private companies, but this does not apply to private companies in the U.S. Only when they go public via an IPO U.S.-based companies have to disclose their financial statements. Therefore, to the extent that financials are less available for U.S. companies when they are still private, the financials of U.S. migrant companies should be biased upward. However, again this is not critical in our context as we are measuring an upper bound. For example, if we find that revenues do not increase after U.S. migration, and they are upward biased, we can be very sure that increasing revenues are not the main benefit of the U.S. ecosystem.

3.2.2 Measuring Innovation

I also measure the innovation output of startups. If innovation inputs are a key difference between the U.S. and European startup ecosystems, startups migrating to the U.S. should improve their innovation performance.

An extensive innovation literature shows that patenting activity reflects firm innovation, so that patenting activity is a widely accepted measure of innovation (Hall, 2000). The first innovation measure is the stock of all (eventually granted) patents by company and year. To also capture the quality of patents, I use the number of citations that a patent receives from other patents (Hall et al., 2005). To account for differences in citing behaviour across countries and years, I scale the citations of a patent by the average citations that all patents receive that are filed in a patent office-times-year, similar to Bernstein (2015). The variable "Scaled citation-weighted patents" is then obtained by adding up all citation-scaled patents held by a company in a year.

To get startups' patents and their citations, VentureSource is merged with the European Patent Office's (EPO) PATSTAT database. PATSTAT aggregates patent data from national

[7]In few cases of the VenutureSource financial data (about 2% of observations), a range was given instead of exact data. I applied a consistent rule to transform these ranges into point estimates. For a specific range, I used the matching records from the other databases and use the average exact value for this range (e.g., 4.6m was assigned whenever the reported range was 1-10m).

patent authorities in over 80 countries, including the U.S., Japan, and European countries (Block et al. (2014)). Overall, 30% of all startups in the sample filed for at least one (eventually granted) patent.

3.2.3 Identifying Startup Exits

The most successful startups typically go public via an IPO. While there are examples of successful startups that exit through an acquisition rather than an IPO, on average, startups who IPO are worth more (Cochrane (2005)), grow more (Poulsen and Stegemoller (2008)), and generate the highest returns for their investors (Cumming and MacIntosh (2003)). All of the VC-funded companies that later became the most successful in the world (e.g., Microsoft, Facebook, Google, Amazon) exited via IPO. If the U.S. IPO market is a key building block behind this success, then startups migrating to the U.S. should also benefit from a higher IPO probability. Nevertheless, large acquisitions may also be an important factor of the U.S. ecosystem, so I include successful acquisitions as a second performance indicator. In particular, I define "successful exit" as either IPO and acquisition with a reported value of more than two times VC invested. The third and fourth measures of exit performance are the company valuation in the event of an IPO or a successful exit.

While VentureSource's coverage of startup exits is better that that of other databases (Maats et al., 2011), is is not complete. I augment VentureSource exit data by a merge with Refinitiv's SDC New Issues and SDC Mergers & Acquisitions datasets, as well as a manual web search of all individual startups in the sample as part of our manual HQ-migration research (in particular, using company website & Crunchbase profiles). The two SDC databases are the industry standards for IPOs and M&As, respectively, and Cruncbhase is a popular wiki-site with detailed information on startups. Overall, 776 additional exits (a 25% increase) result from this search.

3.3 Summary Statistics

The final sample consists of 11,066 European startups, of which 555 (5% of the sample) moved their HQ to the U.S. during the sample period.[8] Table 1 provides summary statistics for most variables used in this paper (variable descriptions can be found in Table A1). On average, U.S. relocations occur 1.6 years after first VC funding (median 1 year after), suggesting that U.S. relocations are generally an early step a company's life cycle.[9]

Table 2 presents descriptive statistics, separated by startups staying in Europe and "U.S. migrants", i.e. startups that moved their headquarters to the U.S. during their lifetime. The paper's results are all foreshadowed in this table. U.S. migrants raise much more funding and innovate more than staying startups. However, revenues do not increase following migration and net income is even significantly lower for migrants. Moreover, migrants are not any more likely to reach an IPO, despite their fundraising advantage. These results already suggest that biggest challenges to European startup performance are the financing market and to a lesser extent innovation inputs, while product and exit markets do not seem to hinder European startups very much.

It is important to note, however, that U.S. migrants are different than stayers in several dimensions already at first funding. As shown in Panel A of Table 2, U.S. migrants are, among others, more often backed from U.S. VCs and more often software firms. The results that follow control for these differences in a variety of ways.

4 Selection into U.S. Migration

I start the empirical analysis by examining what kind of startups select into U.S. migration. Recall from section 2 that the upper bound argument only holds if there is no adverse selection of startups going to the U.S. If adverse selection were the case, the cross-section would give a downward biased upper bound–a bound that is not very useful. However, if the migration of startups is similar to the migration of individuals, a positive selection of

[8] Overall, 647 startups relocated their HQ across borders, with the vast majority, 555, or 86% of all migrants, moving to the U.S. and 92 moving within Europe.

[9] The average age at U.S. migration is 4.2 years (median 3); the average age at first VC funding is 2.6 years (median 2).

startups can be expected to move from a less developed startup ecosystem (Europe) to a highly developed one (like the U.S.). For individuals, the phenomenon that in particular high-skilled individuals migrate from low to high development countries is referred to as "brain drain/gain". Reasons for the disproportionate migration of high-skilled individuals are that they are better paid for their skills abroad (an argument that dates back to at least Hicks (1932)), agglomeration effects, or productivity spillovers (Kerr et al. (2016)).[10]

To analyze selection into migration I estimate a regression model relating observable characteristics at the moment of first VC funding to an indicator of whether the startup moved headquarters to the U.S. The following characteristics, all observed at first VC funding, proxy for startup quality and should, all else equal, be indicative of a higher likelihood of success: the amount raised, whether the startup already generates revenue, the number of VCs investing, the involvement of an U.S. VC, and the number of patents held. All continuous variables are included as the logarithm of one plus the variable. The model is estimated by ordinary-least-squares (OLS), meaning that coefficients are increases in the likelihood of migration per unit increase of the independent variables. Standard errors are clustered at the industry-year level to account for the clustering of U.S. migration in industries and years.

Table 3 presents the results. As expected, I find that measures of startup quality are, if anything, positively correlated with U.S. migration. In Column (1), I relate the log of the amount raised in the first VC round to the likelihood to migrate to the U.S. The model includes fixed effects (FE) for the industry sector, year of first funding, and country in which the startup was founded.[11] The coefficient is highly significant and indicates that U.S. migrants receive more funding already in their first funding. To the extent that the funding amount–within a certain industry, year, and country– is indicative of future performance,

[10]Sports is a good example of how global outliers in terms of skill concentrate in few places, as outlined by Kerr et al. (2016). The U.S. NBA, the world's top-selling and most popular basketball league, attracts the best players from every country in the world. In the season 2021/2022 the NBA rosters feature 109 international players from 39 countries, which are typically among the best in their home countries (See `https://www.nba.com/news/nba-rosters-feature-109-international-player` (accessed on 09/03/2022)). The reason for their migration is likely a combination of higher pay for skills, educational opportunities, and productivity spillovers. For example, Dirk Novitzki is not only better paid at the Dallas Mavericks than at his hometown club, he likely developed his human capital better and is more productive when among other world-class players.

[11]Industry sectors are: "IT: Software", "IT: Hardware", "Biotechnology/Medical", "Consumer/Retail", and other. First funding year fixed are 15 dummy variables for the year of first funding from 2000-2104. Country fixed effects are dummy variables for the 17 countries in which the startup was initially located.

this means that a positive selection of startups migrates to the U.S.

In Columns (2) to (5), I test how other measures of startup quality are related to U.S. migration. I find that U.S. migrants are: backed by more VCs, more often backed by U.S. VC, and have more patents at the moment of first funding. Only the variable indicating whether a startup already generates revenues at first funding is not significantly related to U.S. migration. Since no single startup quality measure is negatively related to migrations, I find no evidence of adverse selection into U.S. migration.

Overall, the results show that there is positive sorting, whereby startups with the greatest potential select to move to the U.S. Importantly, I find no evidence of adverse selection of startups into U.S. migration, which is important because it confirms the upper bound argument from section 2.

5 Moving to the U.S. and Startup Performance

In this section, I compare the performance of startups moving to the U.S. with those staying in Europe. In particular, I compare the performance in five different areas: fundraising, innovation, commercial success, exit likelihood, and scale at exit. To compare the performances, I regress performance in a certain year (in most analyses, in year 6 after initial VC) on a dummy variable indicating whether the startup moved to the U.S. Since migration is concentrated around the year of first funding (the median migrant moves 1 year after first VC, and 76%, have moved by year three after initial VC), I compare migrants and stayers starting from initial funding. All continuous variables are log-transformed (after adding 1), to mitigate the impact of outliers. In all regressions, standard errors are clustered at the industry-times-year of first funding level, because performance of startups starting at the same time in the same industry may be correlated.

5.1 U.S. Migration and Fundraising

Figure 1 plots the fundraising performance, measured as average cumulative VC raised (in 2012 $ m) and average cumulative number of VC rounds received, over the years after first VC funding. The two lines each represent the sample of startups moving to the U.S. and

those staying in Europe. It can be seen that U.S. migrants and stayers start at similar levels of funding at initial VC funding. The average initial difference in the funding amount is not statistically significant (see Panel A of Table 2).

After the initial funding/migration, U.S. migrants grow more in funding raised relative to staying startups. While U.S. movers and staying startups each raised an average of about $6 million at initial funding, U.S. movers had raised an average of $24 million six years later. By comparison, startups staying in Europe raised $12 million by that time. Up to eight years after initial VC, we continue to see steeper funding growth among U.S. movers than startups in Europe. After that, both curves flatten and converge towards the final average funding amount of $31 million for U.S. movers and $13 million for startups staying in Europe.

Regression results in Table 4 quantify the fundraising difference between U.S. migrants and stayers formally. The dependent variable is (the natural logarithm of) cumulative funding raised by year $t+6$, with t being the year of first funding. The variable of interest "Moves to U.S.", is an indicator of whether the startup migrated to the U.S. In Column (1), with no controls, the coefficient on the "Moves to U.S." dummy indicates that U.S. movers raise on average 183% more VC than European stayers ($= e^{1.04} - 1$). However, firms may fundamentally differ in their external funding needs depending on their industry sector, stage, and geography. If any of these factors also drives U.S. migration, the estimates in Columns (1) do not reflect an advantage of the U.S. ecosystem. To account for these differences, Column (2) adds fixed effects for the year, industry, stage, and source country, all at first funding. In addition, Column (3) controls for observable characteristics at first funding using all variables used in the most comprehensive selection model of Table 3. These controls, all measured at initial funding, include: the initial VC amount raised, startup age, number of VCs, U.S. VC involvement, stage, and number of patents.

In all three columns, the coefficient on "Moves to U.S." indicates that startups moving headquarters to the U.S. raise orders of magnitude more funding after migration than startups staying in Europe. The effect is large and statistically different from zero at the 1% level across all specifications. Depending on the controls, U.S. migrants raise between 86% and 210% more funding by year 6 after first funding.

To understand whether the fundraising advantage is driven by U.S. migrants receiving

more more rounds or more funding per round, I also use the natural logarithm of the number of VC rounds by $t+6$ as a dependent variable in Columns (4) to (6). The estimated coefficient is 0.2 and highly statistically significant. This suggests that U.S. migrants receive approx. 22% more rounds than stayers. Hence, the overall fundraising advantage is driven by a mix of both factors: receiving more rounds and more funding per round in the U.S.

Overall, and not surprisingly, we find that startups migrating to the U.S. raise orders of magnitude more funding over time than startups staying in Europe.

5.2 U.S. Migration and Innovation

Figure 2 shows the average cumulative number of patents (eventually granted) over years after first funding, again broken down by U.S. migrants and European stayers. We see that both groups start from about the same level in the first funding year, at approx. 0.6 patents. That is, migrants and stayers do not differ in in number of patents at first funding (see Panel A of Table 2). In the years after first funding, however, U.S. migrants grow their patent stock more than European stayers. The difference is such that 6 years after first funding, U.S. migrants hold on average about 0.9 patents more than European stayers.

Table 5 shows regression results that quantify the differential development in innovation performance. In Column (1), without controls, we find that U.S. migrants hold about 19% more patents by year 6 after first funding. This difference is significant at the 1% level and does not change much when controlling for year, country, industry, stage and observable characteristics at first funding (including the number of patents at first funding) in Columns (2) and (3).

A simple patent count may not account for the quality of patents. But even when weighting patents by their received citations, U.S. migrants innovate more than European stayers after first funding. In fact, the difference becomes even larger when considering patent quality. Columns (4) to (6) show the results when using the log number scaled citation-weighted patents, by year 6 after first funding, as dependent variable. Results show that U.S. migrants have between 26% and 35% more citation-weighted patents six years after first funding, compared to startups staying in Europe.

5.3 U.S. Migration and Commercial Success

Next, I examine whether U.S. migration is related to higher commercial success. I use two measures of commercial success: revenue and net income (both in 2012 USD). Both measures emphasize a different type of commercial success: revenue reflects product market success, while net income reflects profitability of the business.

Figure 3 shows how revenue and net income evolve over time from initial funding, separated by U.S. migrants and stayers. We can see that U.S. migrants have, surprisingly, lower revenue than stayers in Europe over a long period after initial funding. It is not until year nine after initial financing that the revenue lines cross, and U.S. migrants show higher revenues from then on. In terms of net income, both groups show a "J-curve" (albeit a noisy one), meaning that startups first go through a period of net losses before they enter the path towards profitability. U.S. migrants, however, appear to ride a "deeper" J-curve, with higher financial losses over a longer period but higher profits at the end.

Table 6 shows that U.S. migration does not lead to higher revenues in many years after migration - also in a regression framework. Instead, U.S. migration is related with higher financial losses over a an extended period of time. The dependent variables are now revenue and net income six years after first funding. As revenue and net profit can be negative, I cannot use the logarithm as before, and therefore winsorize both variables at the 2.5% and 97.5% ends to control for outliers in the regression estimates. The results in Columns (1)-(3) show that U.S. migrants, compared to staying startups, do not significantly increase their revenues by year 6 after initial funding.[12]

Columns (4)-(6) show that, instead, U.S. migration is associated with higher losses after initial financing. The coefficients are absolute values and indicate that U.S. migrants sustain anywhere between 0.9-1.6 million higher losses in year 6 after startup than startups staying in Europe. This difference is highly statistically significant across models.

Overall, the results in this subsection show that U.S. migration is not associated with higher immediate sales success but, on the contrary, with higher financial losses. This result is surprising and an important finding of this paper. With better startups going to the U.S.

[12] U.S. migration is not associated with higher revenues anywhere between 1 and 8 years after initial funding (see section 6).

(see section 2 and section 4) but not immediately increasing their sales, we can conclude that the product market is not an immediate disadvantage of the European startup ecosystem. If anything, the U.S. ecosystem seems better suited to withstand higher losses, consistent with the much better funding of U.S. migrants.

5.4 U.S. Migration and Exits

The most successful startups usually go public or exit through mergers and acquisitions (Cumming and MacIntosh, 2003; Puri and Zarutskie, 2012; Ewens and Marx, 2018; Chen et al., 2021; Yimfor and Garfinkel, 2023). As the U.S. hosts arguably the most developed market for IPOs and M&As in recent decades, European startups may mainly migrate to the U.S. to increase their chances of reaching a successful public offering or acquisition.

Surprisingly, however, I find that U.S. migrants do not benefit from a higher IPO probability. The average IPO rate of U.S. migrants is 4% and lower than the 4.7% of European stayers, as shown in Table 2. The regression results in Table 7 quantify the difference in a regression framework. In Column (1), with no controls, the coefficient on "Moves to U.S." reflects the cross-sectional difference of U.S. migrants of 0.7%. This difference is marginally significant at the 10% level. However, the difference in IPO rates loses its statistical significant when controlling for differences country, industry, and year (Column (2)), as well as when controlling fro observables at first funding in Column (3).

The left panel of Figure 4 plots the cumulative IPO probability for U.S. movers and stayers over time. At any point after first VC, U.S. migrants have a lower IPO likelihood than startups staying in Europe. Also, the curve of U.S. migrants is shifted to the right in that U.S. migrants execute their IPO later on average. For example, the majority (approximately 2/3) of IPOs of startups staying in Europe takes place between 0 and 6 years after first VC funding. However, most U.S. movers' IPOs (approximately 2/3) occur between 6 and 10 years after first VC funding. Although U.S. movers catch up in IPOs between years 6 and 10, they can never close the gap, so startups staying in Europe are more likely to reach an IPO overall.

It may be that U.S. migrants substitute IPOs with successful acquisitions because the U.S. M&A market offers large advantages for migrants. To understand whether this is the case,

I test whether U.S. migrants are more likely to reach a "successful exit", which comprises both IPOs and acquisitions with a reported valuation of more than twice VC raised (Yimfor and Garfinkel, 2023). Columns (4) to (6) of Table 7 present the results. The coefficient is positive but loses its significance when controlling for observable differences at first funding. This indicates that conditional on having comparable funding, investors, stage, and patents at the outset, U.S. migrants are not any more likely to achieve a successful exit compared to stayers.

Overall, Table 7 highlights the fact that startups moving to the U.S. are not any more likely to reach an IPO or successful exit than comparable startups staying in Europe. This indicates that U.S. migrants do not benefit from better exit markets. This result is puzzling because U.S. movers raise much more funding and innovate more after moving. To resolve this paradox, I now analyze the degree of success of companies that perform well.

5.5 U.S. Migration and Firm Scale at Exit

We have seen that companies that relocate their headquarters to the U.S. experience a greater increase in funding and innovation than companies that remain in Europe. However, it is unclear why this advantage does not translate into a significantly higher probability of a successful exit. One explanation could be that the degree of success of companies that relocate to the U.S. and succeed is greater than that of European startups. To analyze this possibility, I now compare the value and scale of firms that achieve an exit.

Table 8 reports estimates from company-level regressions where the dependent variables are either the (1) valuation, (2) employees, (3) revenue, (4) net income, or (5) company age, in the moment of a successful exit. I use the natural logarithm of one plus these variables– except for net income, since it can be negative. As in the most restrictive models in Table 4 to Table 7, all regressions include company industry, year, and country fixed effects, as well as observable characteristics at first funding (i.e., VC amount raised, startup age, number of VCs, U.S. VC involvement, stage, and number of patents at first VC funding).

Column (1) reports the difference in company valuation between U.S. migrants and European stayers in the moment of IPO or successful exit (in Panel A or B, respectively).[13]

[13]For IPOs, company valuation is calculated as shares outstanding after offer times offer price. For acquisi-

I find that U.S. migrants have higher company valuations on the day of IPO or successful exit. This difference is statistically significant at the 1% level. The coefficient implies that startups moving headquarters to the U.S. are worth 4.4 *times* times the value of startups reaching an IPO in Europe ($= e^{1.48}$). This difference remains huge when considering both IPOs and successful acquisitions together as successful exits. The company value of U.S. migrants is 2.4 times that of European stayers at a successful exit, as implied by Column (1) of Panel B.

Columns (2) and (3) show that U.S. migrants are also of much bigger scale at exit, compared to European stayers. Firme scale is measured as number of employees and revenue in Columns (2) and (3), respectively. The results show that firms moving to the U.S. have 3.8 times more employees and 4.1 times more revenue at IPO compared to startups reaching an IPO in Europe. Similarly, U.S. migrants have 2.2 times more employees and 2.4 times more revenues than their European counterparts in case of a successful exit.

Columns (4) shows that U.S. migrants are less profitable at IPO and successful exit than European startups reaching such exits. The differences are highly statistically significant and indicate that U.S. migrants have on average 3.7 million U.S. dollar lower net income at IPO, and 2.2 millions lower net income at successful exit. Since the average net income at exit in the sample is negative (mean: -3.1 USDm, median: -0.5 USDm), this means that U.S. migrants have much higher net losses than European stayers.

Finally, the question remains whether U.S. migrants reach their enormous scale in the same time frame as European startups or whether higher VC funding leaves them more time to scale before an exit. Therefore, Columns (5) reports the same regressions as before, with the only difference that the (natural logarithm of) age at IPO/successful exit is the dependent variable. The coefficients imply that U.S. migrants are 42% older at IPO and 16% older at successful exit than their European equivalents. These differences are similar in the descriptive statistics. While European startups are on average 8.6 years old at IPO, U.S. migrants are 11.2 years old at IPO (i.e., 30% older).

tions, the transaction value is used.

5.6 Mechanism

Results until here suggest that the salient difference between U.S. migrants and European stayers is more funding and the ability to tolerate higher financial losses. I present three pieces of additional evidence that: 1) the funding advantage explains most of the other differences, 2) shareholders show indeed greater loss tolerance, and 3) the difference is more likely a U.S. advantage than a European disadvantage.

5.6.1 Fundraising Advantage as Main Mechanism?

How much of the relationship between U.S. migration and company outcomes can be explained by the fundraising advantage? To answer this question, I re-estimate the same regression models of startup performance as in Table 5 to Table 8, but now add the amount of cumulative funding raised by the time of the dependent variable as an explanatory variable. The change in the "Moves to U.S."-coefficient should give us an indication of how much of the performance difference can be explained by the financing advantage.

The results in Table 9 show that much of the higher performance of U.S. migrants can be explained by their financing advantage. For example, the coefficient on the number of patents drops by 50% from 0.12 (in Column (3) of Table 5) to 0.06 in Column (1). Similarly, the effect on net income becomes insignificant (Column (4)), meaning that the relationship between U.S. migration and higher net losses can be entirely explained by the financing advantage. Also the relationship between U.S. migration and successful exits is explained away by the financing advantage. Last, the valuation at exit coefficients in Columns(7)-(8) drop by approx. 50% after controlling for the financing advantage. Taken together, these results suggest the fundraising disadvantage explains a major part of the overall European disadvantage at startup performance.

5.6.2 Loss Tolerance?

I argued that the higher net income losses of U.S. migrants stand for higher tolerance for losses in the U.S. startup ecosystem. However, this is not necessarily the case if only startups with eventually successful exits accumulate more losses. Only if U.S. migrants even receive

more funding if they eventually fail, shareholders would have to tolerate more losses. To test this hypothesis, I differentiate between startups that failed and startups that were eventual successes, i.e. IPOs or successful exits, from an ex post point of view.

Table 10 reveals that U.S. migrants that eventually failed show a similar development pattern to those that were eventually successful. Specifically, they receive virtually the same funding boost (Columns (1)-(2)), produce even more innovation than successful U.S. migrants (Columns (3)-(4)), experience no increase in revenues (Column (5)), and show higher financial losses than European stayers (Column (6)).

In essence, U.S. migrants receive the same benefits from moving, regardless of whether they ultimately succeed or fail.This evidence supports the interpretation that higher financial losses in the U.S. ecosystem indeed reflect a higher tolerance for failure, rather than just a characteristic of successful startups.

5.6.3 U.S. Advantage or European Disadvantage?

I use the heterogeneity of 17 origin countries in the sample to understand whether the differential development is rather due to the target country (a U.S. advantage) or the origin countries (a European disadvantage). If it was more due to origin countries, we would expect to observe some country heterogeneity, for example that startups from the most developed European ecosystems (like the UK) benefit less from moving.

Table 11 shows that the development of U.S. migrants is remarkably similar across origin countries. Panel (A) and (B) split the sample into the most and least developed startup ecosystems, as defined by the country VC-to-GDP ratio.[14] I find that U.S. migrants develop in virtually identical ways independent of whether they are from the most developed (GB, SE, IE, FI, CH) or the least developed VC markets. Similarly, U.S. migrants develop almost identically if they are from countries with higher or lower average risk-taking cultures (Panels

[14]Using the country VC-to-GDP ratio is in the spirit of the financial development literature, that measures financial development of a country as the ratio of stock market capitalisation (plus credit market) to GDP (Rajan and Zingales, 1998). Policymakers too often use VC-to-GDP to compare the development of VC markets (see, for example, https://ec.europa.eu/programmes/horizon2020/en/news/assessing-potential-eu-investment-venture-capital-and-other-risk-capital-fund-funds, accessed on 28 June 2021). Total VC investment is calculated as the sum of all deal amounts in a country and year based on all deals reported by VentureSource. GDP data are from Refinitiv Datastream.

(C) and (D)).[15] Even startups from the UK only, often cited as the second-best startup ecosystem worldwide, benefit similarly from moving to the U.S. as the general population (see Table A7).

In summary, the homogeneous development pattern of U.S. migrant startups across diverse countries of origin suggests that the benefits are more likely due to the U.S. being special (i.e., a U.S. advantage), rather than the origin country conditions driving the result.

6 Robustness

Overall, we found that the main performance differences of startups moving to the U.S. is more financing, that allows to reach a larger scale under the accumulation of higher losses over longer time periods. However, these factors are not necessarily due to the ecosystem in the U.S., but could be the result of a selection of startups moving to the U.S. If true, this implies that the U.S. startup ecosystem has no advantages over the European ecosystem in terms of facilitating startup success. Given the overwhelming startup success in the U.S., it seems unlikely that the U.S. ecosystem does not offer any advantages. This chapter summarizes robustness tests of the main results, including analyses may shed some light on the role of selection vs. treatment.

6.1 Matched Sample

One way to disentangle selection and treatment effects would be use a closely-matched control group of similar firms at migration. Such matching approach exploits the fact that the sample of non-migrants is many times larger (about 20x) than the migrant sample, allowing to identify highly similar control firms as counterfactual sample. However, while matching results might be closer to the actual treatment effect of the different ecosystems, I refrain from denoting these effects as causal.

The idea is to form a control group that is as similar to migrants as possible, with the only difference that they do not migrate to the U.S. To form such a control group, I choose

[15] Countries are split according to whether their people have above or below average risk-taking preferences as measured in a global survey by Falk et al. (2018).

the nearest neighbor - among all non-migrants that are active in the same industry and are in the same stage in the migration year - on cumulative VC raised, cumulative number of rounds, age, number of VCs invested, an indicator of whether the startup is backed by U.S. VC, and an indicator of whether the startup has at least one patent, based on Mahalanobis distance (Rubin, 1980).[16] All startups that are active, that is, all that have started but not yet exited, are considered as a potential match for one migrant in its migration year. The approach can identify a matching control firm for all 555 migrants. Table A9 reports the means of startup characteristics in the match(=migration) year, together with a test for differences. After matching, treatment and control samples are indistinguishable along observables.

Figure A1, Figure A2, Figure A3 Figure A4 provide a graphical impression how U.S. migrants perform compared to matched control firms in terms of fundraising, innovation, commercial success, and exit success, respectively. The development paths before the migration year are largely parallel, but after migration, development paths deviate in a similar fashion as in the overall sample: After migration, migrants perform much better in fundraising, slightly better in innovation, revenues do not increase much for at least 7 years after migration, and net income becomes more negative. Regression results only change slightly compared to the overall sample. Table A10 to Table A13 repeat the same analysis from Table 4 to Table 7, except for now using the matched control sample. U.S. migrants still raise between 72-112% higher funding in the years after migration compared to the closely matched control sample. This effect is again highly statistically significant. However, the U.S. migration effects on commercial and exit success become generally insignificant when using a closely matched control group. Overall, these results corroborate the interpretation that the financing advantage in the U.S. is the key difference versus the European startup ecosystem.

[16] I use a multivariate distance measure instead of a univariate distance measure based on a prediction model (like propensity score (Rosenbaum and Rubin, 1983)), because many industry-stage-year cells contain only few migrants, and these would all have to be dropped from the sample because of perfect prediction.

6.2 U.S. Migration or U.S. Investment?

Is U.S. investment driving the U.S. migration result? In all main regressions, I control for U.S. VC involvement at first funding, and this does not affect the migration coefficients. However, it might be that eventually all U.S. migrants are U.S. VC backed, so there is little variation among migrants. To understand whether U.S. VC investment leads to similar results as U.S. migration, I test whether European stayers follow a similar development pattern as U.S. migrants when they receive U.S. investment. I test this hypothesis by restricting the sample to European stayers. Now the variable of interest is whether the startup received U.S. VC funding in its first round or not (8% of 10,511 stayers receive early U.S. VC). Table A8 shows that U.S. investment in European startups does not lead to a similar development pattern as U.S. migration. European stayers that receive U.S. VC raise more funding, increase their revenues, and are more likely to exit. However, they do not innovate more, do not increase their financial losses, and are not of a bigger scale in the moment of exit. As such, U.S. VC-backed European stayers are less risky projects, not more risky ones like U.S. migrants.

I conclude that U.S. VC-backed European stayers do not follow a similar development pattern as U.S. migrants. This is suggestive evidence that the U.S. startup ecosystem is special in how it nurtures its startups, and this specialty may not be easily exported through U.S. VCs investing abroad.

6.3 Other Robustness Checks

I conduct additional robustness checks to examine the extent to which the main differences are due to selection:

- In the main analysis, I use all U.S. migrants regardless of when they migrate (e.g., before, after first funding, or even just before exit). This is justified by the fact that migration happens on average very early, so that startups spend enough time in the respective ecosystem. For example, remember that 420 of the 555 migrants (or 76%) have already migrated by year 3 after first funding. However, results are qualitatively and quantitatively similar when only considering the 420 early migrants who moved up to three years after first funding (Table A4). That is, results are not driven by late

migrants moving shortly before an impending exit.

- The decision to investigate performance in year 6 after first funding is admittedly ad-hoc. However, consistent with the graphical evidence, the results are qualitatively and quantitatively similar when analyzing any year between 3 and 8 years after first funding (see Table A5 and Table A6 for year 4 and year 8, respectively).

7 Conclusion

This paper explores the main drawbacks of the European startup ecosystem using a new dataset on European startups moving to the U.S. I argue that since the more promising startups migrate to the U.S., the difference between migrants and stayers provides an upper bound on the advantage of the U.S. startup ecosystem relative to Europe. This allows to (partially) identify the main European disadvantages at startup performance.

Empirical evidence shows that startups moving to the U.S. receive much more capital, produce slightly more innovation, and are grow much bigger before exit than startups staying in Europe. More surprisingly, I find that U.S. migrants do not increase their revenues for many years after migration, instead incur higher financial losses throughout, and do not significantly improve their likelihood of achieving an IPO or successful exit. Additional evidence shows that large parts of the innovation, net income loss, and growth difference can be explained by U.S. migrants' funding advantage.

I view these results as contributing to our understanding of the main European disadvantage at startup performance in showing that European startups are only marginally, if at all, hindered by technology, product, and exit markets, but that the main disadvantage is the VC financing market. This is consistent with the perception that markets for technology, consumer product, IPOs and M&As are highly globalized (Erel et al., 2012; Doidge et al., 2013; Audretsch et al., 2014; De Marco et al., 2017), but the VC market requires a certain degree of locality (Chen et al., 2010; Cumming and Dai, 2010; Lutz et al., 2013).

The findings of this paper have important implications for entrepreneurs and policymakers seeking to enhance the performance of their startups. Encouragingly, the results suggest that improving the European startup ecosystem is much more straightforward than previ-

ously thought. Instead of orchestrating comprehensive efforts across multiple markets, such as product, IPO, and acquisition markets, policymakers can derive significant benefits by strategically concentrating their efforts on the venture capital market. These findings hold a promise for effectively fostering startup innovation in Europe.

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Figure 1: Moving to the US and Fundraising

The sample consists of 11,066 startups from 17 European countries that received venture capital financing between 2000 and 2014 according to VentureSource. The firms are tracked from the year of first VC funding up to 2021. All performance indicators are measured as average cumulative total up to year t.

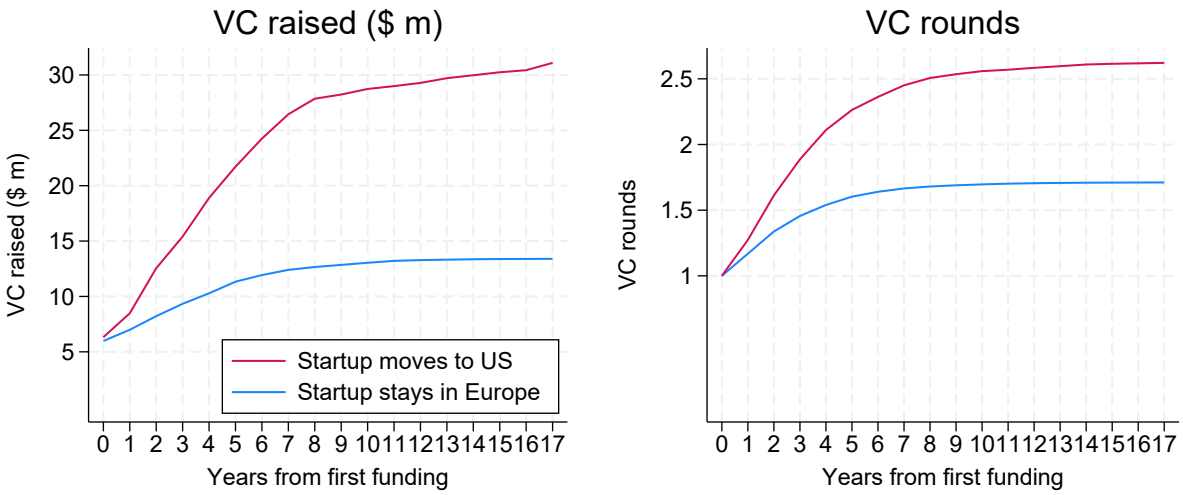


Figure 2: Moving to the US and Innovation

The sample consists of 11,066 startups from 17 European countries that received venture capital financing between 2000 and 2014 according to VentureSource. The firms are tracked from the year of first VC funding up to 2021. All performance indicators are measured as average cumulative total up to year t.

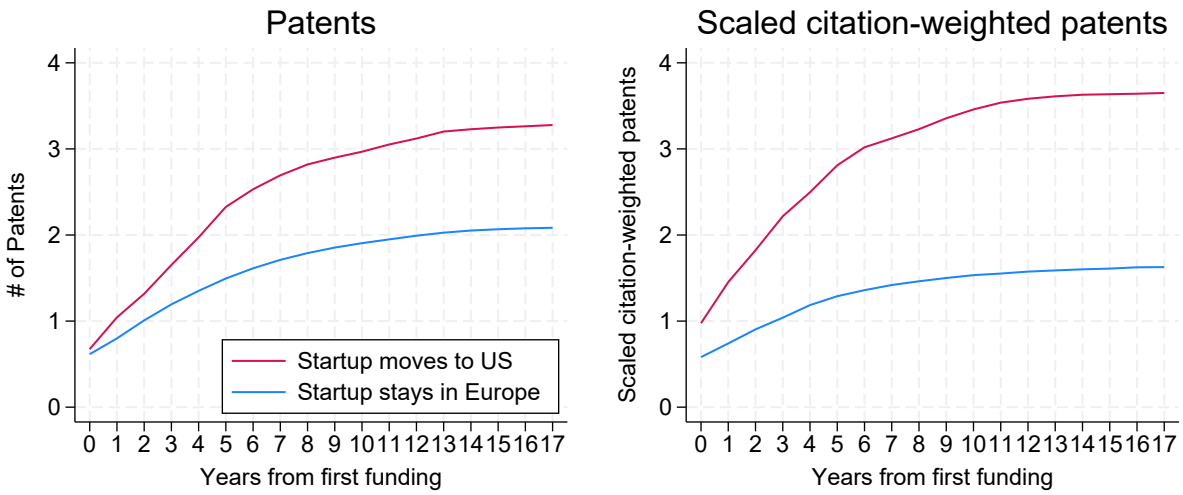


Figure 3: Moving to the US and Commercial Success

The sample consists of 11,066 startups from 17 European countries that received venture capital financing between 2000 and 2014 according to VentureSource. The firms are tracked from the year of first VC funding up to 2021. All performance indicators are measured as average in year t.

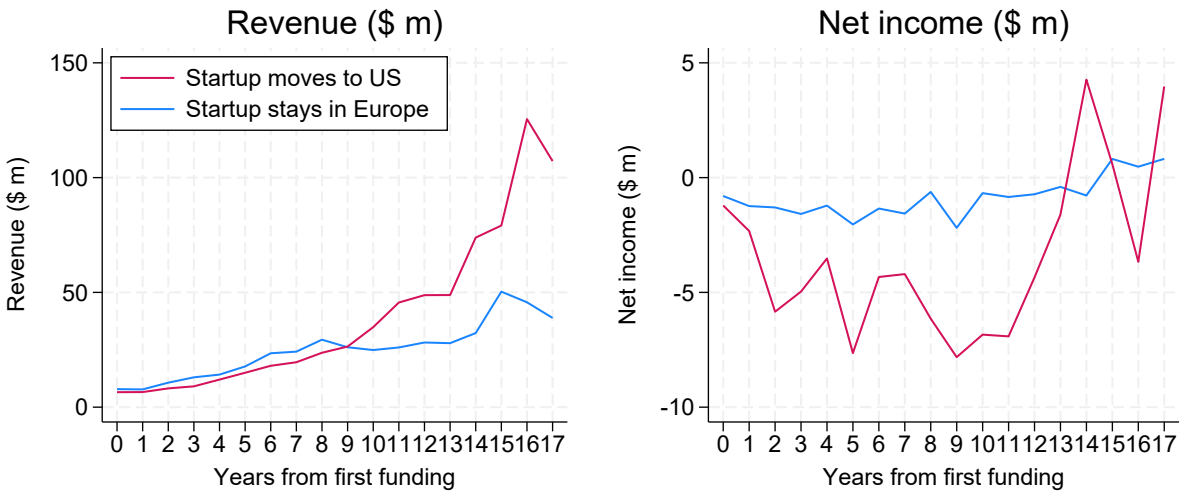


Figure 4: Moving to the US and Exit Success

The sample consists of 11,066 startups from 17 European countries that received venture capital financing between 2000 and 2014 according to VentureSource. The firms are tracked from the year of first VC funding up to 2021. All performance indicators are measured as average cumulative total up to year t.

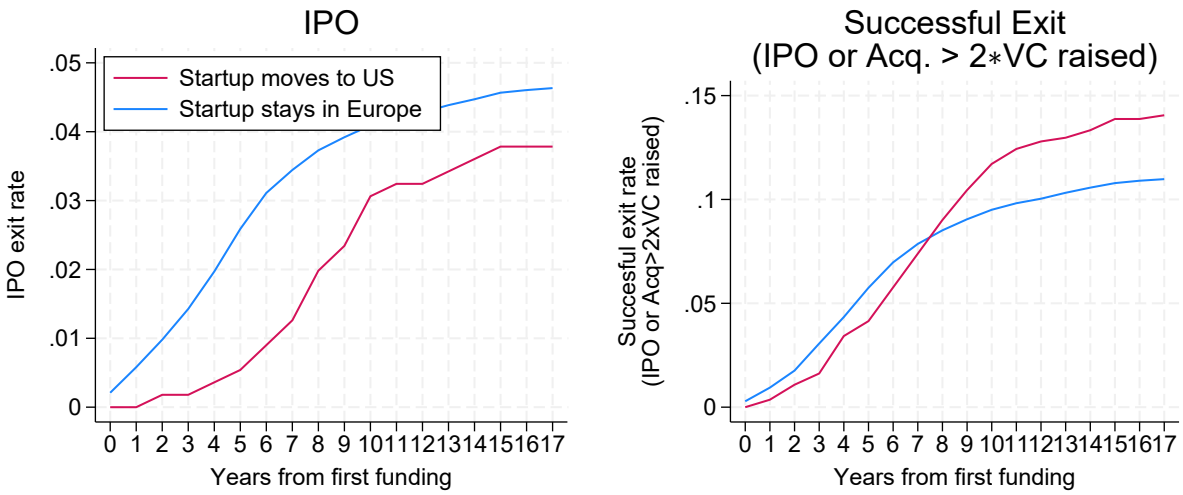


Table 1: Summary Statistics

This table presents summary statistics on the companies in the sample. The sample consists of 11,066 startups from 17 European countries that received first venture capital financing between 2000 and 2014 according to VentureSource. Panel A presents startup characteristics at first VC funding. Panel B summarizes headquarter (HQ) migration statistics that were hand-collected from several sources as described in the text. Startups are categorized as "Moves to US" if they moved their HQ location to the US during their VC funding period. Panel C contains measures of startups' final performance as of July 2021. The first VC funding year is defined as $t = 0$. $ values are in 2012 USD.

	Obs.	Mean	Median	SD	Min	Max
Panel A: Startup characteristics at first funding (t=0)						
VC raised ($ m)	11066	5.74	1.64	26.43	0.00	1178.00
Pre-money valuation ($ m)	3358	15.37	3.99	91.05	0.00	3208.00
Startup age	11066	2.59	1.80	2.53	0.00	20.39
Num. of VCs investing	11066	1.98	2.00	1.28	1.00	21.00
US VC involved	11066	0.09	0.00	0.29	0.00	1.00
Year of first funding	11066	2006.39	2006.00	4.96	2000.00	2014.00
Revenue ($ m)	3117	6.83	0.55	56.99	0.00	2200.13
Net income ($ m)	2860	- 0.66	- 0.23	4.23	- 64.05	151.20
Employees	3662	49.10	12.00	245.70	0.00	6554.00
Num. of Patents	11066	0.62	0.00	3.20	0.00	198.00
Stage						
Seed	11066	0.12	0.00	0.33	0.00	1.00
Product Development/Clinical Trial	11066	0.26	0.00	0.44	0.00	1.00
Generating Revenue	11066	0.61	1.00	0.49	0.00	1.00
Industry						
Software	11066	0.22	0.00	0.42	0.00	1.00
Hardware	11066	0.11	0.00	0.31	0.00	1.00
Medical/Biotechnology	11066	0.17	0.00	0.38	0.00	1.00
Consumer/Retail	11066	0.21	0.00	0.40	0.00	1.00
Other Industry	11066	0.30	0.00	0.46	0.00	1.00
Country						
France	11066	0.20	0.00	0.40	0.00	1.00
Germany	11066	0.12	0.00	0.33	0.00	1.00
Sweden	11066	0.07	0.00	0.25	0.00	1.00
United Kingdom	11066	0.29	0.00	0.45	0.00	1.00
Other Country	11066	0.32	0.00	0.47	0.00	1.00
Panel B: Migration variables						
Moves to US	11066	0.05	0.00	0.22	0.00	1.00
Age at migration to US	555	4.17	3.00	3.81	0.00	19.00
Panel C: Startup performance						
VC raised ($ m) by t+6	11066	12.55	3.10	44.46	0.00	1412.00
VC rounds by t+6	11066	1.68	1.00	0.98	1.00	7.00
Num. of patents by t+6	11066	1.66	0.00	5.70	0.00	231.00
Scaled citation-weighted patents by t+6	11066	1.44	0.00	8.11	0.00	532.94
Revenue ($ m) in t+6	2802	23.14	2.66	172.09	0.00	5487.07
Net income ($ m) in t+6	2760	- 1.55	- 0.14	17.62	-322.48	492.34
IPO	11066	0.05	0.00	0.21	0.00	1.00
Successful Exit (IPO or Acq.>2*VC raised)	11066	0.11	0.00	0.32	0.00	1.00

Table 2: European Stayers vs. US Movers

This table reports the means of each variable, distinguishing between startups ever moving their headquarters (HQ) to the US and staying startups. Startups are categorized as "Moves to US" if they moved their HQ location to the US during their VC funding period and "Stays in Europe" otherwise. Panel A reports means of startup characteristics measured at first VC funding. Panel B reports startups' final performance measures as of July 2021. All variables are defined in Appendix A1. The last column reports t-statistics of two-sample t-tests for equality of means. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Stays in Europe	Moves to US	Difference	
	Mean	Mean	Mean	t-stat.
Panel A: Startup characteristics at first financing (t=0)				
VC raised ($ m)	5.73	5.93	0.21	0.18
Pre-money valuation ($ m)	15.45	13.39	-2.06	-0.25
Startup age	2.59	2.49	-0.10	-0.88
Num. of VCs investing	1.96	2.36	0.40	7.25***
US VC involved	0.08	0.29	0.21	16.76***
Revenue ($ m)	6.91	5.08	-1.83	-0.37
Net income ($ m)	-0.65	-1.00	-0.35	-0.90
Employees	50.02	30.99	-19.03	-1.01
Num. of Patents	0.62	0.67	0.06	0.42
Stage				
Seed	0.13	0.09	-0.03	-2.22 **
Product Development/Clinical Trial	0.26	0.28	0.02	1.07
Generating Revenue	0.61	0.62	0.01	0.54
Industry				
Software	0.21	0.38	0.17	9.30***
Hardware	0.11	0.11	0.00	0.12
Medical/Biotechnology	0.18	0.12	-0.05	-3.32***
Consumer/Retail	0.21	0.14	-0.06	-3.63***
Other Industry	0.30	0.25	-0.05	-2.56 **
Country				
France	0.20	0.17	-0.03	-1.67 *
Germany	0.13	0.09	-0.04	-2.61***
Sweden	0.07	0.05	-0.02	-1.43
United Kingdom	0.29	0.31	0.02	0.81
Other Country	0.32	0.39	0.07	3.24***
Panel B: Startup performance variables				
VC raised ($ m) by t+6	11.93	24.25	12.32	6.37***
VC rounds by t+6	1.64	2.36	0.72	17.22***
Num. of patents by t+6	1.61	2.53	0.92	3.70***
Scaled citation-weighted patents by t+6	1.36	3.02	1.66	4.70***
Revenue ($ m) in t+6	23.50	18.04	-5.46	-0.41
Net income ($ m) in t+6	-1.35	-4.33	-2.98	-2.23 **
IPO	0.05	0.04	-0.01	-0.76
Successful Exit (IPO or Acq. ¿ 2*VC raised)	0.11	0.15	0.04	2.58***

Table 3: Selection into US Migration

This table reports ordinary-least-squares (OLS) regressions of startups' US migration outcomes on variables measured at first VC funding. The unit of observation is a VC-backed startup. The dependent variable "Moves to US" is one if a startup moved its HQ location to the US during the VC funding period, and zero otherwise. The regressors of interest are measures for ex ante startup quality and US orientation measured in the moment of first VC funding. To build patent measures, only patents applied for by two months before the first VC financing round were considered. All variables are defined in Appendix A1. Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Startup moves to US?					
	(1)	(2)	(3)	(4)	(5)	(6)
LN VC raised ($ m) in first round	0.011***					0.004**
	(0.002)					(0.002)
Stage: Generating Revenue		-0.005				-0.004
		(0.004)				(0.004)
LN Number of VCs investing in first round			0.047***			0.022***
			(0.008)			(0.008)
US VC in first round				0.117***		0.105***
				(0.014)		(0.014)
LN Number of patents at first round					0.013**	0.006
					(0.005)	(0.005)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Funding year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11066	11066	11066	11066	11066	11066
R-squared	0.023	0.018	0.023	0.041	0.018	0.044

Table 4: Moving to the US and Fundraising

This table reports regression results of startup fundraising performance on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The dependent variable is the cumulative VC raised (in $ m) by year 6 after first funding in Columns (1)-(3), and cumulative number of VC rounds in Columns (4)-(6). $t = 0$ is the year of the first VC funding round. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	LN VC raised ($ m) by $t+6$			LN VC rounds by $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	1.04***	1.13***	0.62***	0.22***	0.23***	0.20***
	(0.10)	(0.07)	(0.05)	(0.02)	(0.02)	(0.02)
LN VC raised ($ m) in first round			0.91***			0.01**
			(0.01)			(0.00)
LN Startup age at first round			-0.17***			-0.05***
			(0.02)			(0.01)
LN Number of VCs investing in first round			0.11***			0.09***
			(0.02)			(0.01)
US VC in first round			0.18***			0.03**
			(0.06)			(0.01)
LN Number of patents at first round			0.13***			0.04***
			(0.02)			(0.01)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	11066	11066	11066	11066	11066	11066
R-squared	0.019	0.070	0.677	0.025	0.075	0.103

Table 5: Moving to the US and Innovation

This table reports regression results of startup innovation performance on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The dependent variable is the cumulative number of patents granted by year 6 after first funding in Columns (1)-(3), and cumulative scaled citation-weighted patents in Columns (4)-(6). $t = 0$ is the year of the first VC funding round. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	LN Num. of patents by $t+6$			LN Scaled citation-weighted patents by $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	0.17***	0.22***	0.12***	0.27***	0.30***	0.23***
	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
LN VC raised ($ m) in first round			0.02***			0.02***
			(0.00)			(0.00)
LN Startup age at first round			-0.05***			-0.02***
			(0.01)			(0.01)
LN Number of VCs investing in first round			0.05***			0.03
			(0.02)			(0.02)
US VC in first round			0.03			0.03
			(0.02)			(0.02)
LN Number of patents at first round			1.09***			0.87***
			(0.02)			(0.02)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	11066	11066	11066	11066	11066	11066
R-squared	0.002	0.216	0.662	0.006	0.123	0.464

Table 6: Moving to the US and Commercial Success

This table reports regression results of startup commercial success on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The dependent variable is the revenue in year 6 after first funding in Columns (1)-(3), and net income in Columns (4)-(6). $t = 0$ is the year of the first VC funding round. Revenue and net income are winsorized at the 1% and 99% ends. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Revenue ($ m) in $t+6$			Net income ($ m) in $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	2.31	2.29	0.02	-1.54***	-1.23***	-0.94**
	(2.16)	(2.03)	(1.91)	(0.42)	(0.41)	(0.43)
LN VC raised ($ m) in first round			5.88***			-0.40***
			(0.46)			(0.09)
LN Startup age at first round			-1.10			0.38***
			(0.74)			(0.13)
LN Number of VCs investing in first round			-6.64***			-0.63**
			(1.39)			(0.27)
US VC in first round			5.15**			-0.02
			(2.24)			(0.35)
LN Number of patents at first round			-3.44***			-0.78***
			(0.91)			(0.17)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	2802	2802	2802	2760	2760	2760
R-squared	0.001	0.096	0.215	0.010	0.119	0.161

Table 7: Moving to the US and Exits

This table reports regression results of startup exit outcomes on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The dependent variables are dummy variables indicating whether the startup had an exit via IPO in Columns (1)-(3)/IPO or successful acquisition (i.e., acquisition with valuation larger than $2 * VC_raised$) in Columns (4)-(6), by the end of the sample period (July 2021). $t = 0$ is the year of the first VC funding round. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	IPO			Successful Exit (IPO or Acq>2*VC raised)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	-0.01	0.00	-0.01	0.04*	0.04**	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
LN VC raised ($ m) in first round			0.01***			0.02***
			(0.00)			(0.00)
LN Startup age at first round			0.01			0.00
			(0.00)			(0.01)
LN Number of VCs investing in first round			-0.01			-0.01
			(0.00)			(0.01)
US VC in first round			0.01			0.03
			(0.01)			(0.02)
LN Number of patents at first round			0.02***			0.03***
			(0.00)			(0.01)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	11066	11066	11066	11066	11066	11066
R-squared	0.000	0.037	0.050	0.001	0.029	0.046

Table 8: Moving to the US and Scale at Exit

This table reports regression results of startup exit outcomes on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The dependent variables are measures of firm scale at exit: valuation (market cap at IPO or deal value at acquisition), number of employees, revenue, and net income, as well as firm age. Panel A includes only IPO exits and Panel B includes all successful exits, i.e., IPOs and acquisitions at a valuation of more than 2 times VC raised. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	LN Valuation at Exit	LN Employees at Exit	LN Revenue at Exit	Net income ($m) at Exit	LN Age at Exit
Panel A: IPOs					
Moves to US	1.48***	1.34***	1.18***	-3.65***	0.41***
	(0.27)	(0.39)	(0.39)	(1.24)	(0.07)
Observations	495	422	414	402	512
R-squared	0.461	0.476	0.547	0.397	0.368
Panel B: Successful Exits					
Moves to US	0.89***	0.77***	0.75***	-2.18**	0.20***
	(0.14)	(0.19)	(0.18)	(1.00)	(0.05)
Observations	1225	956	801	741	1242
R-squared	0.379	0.342	0.427	0.306	0.278
First funding controls	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes

Table 9: Funding Advantage as Main Mechanism?

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8, with the only difference that I the cumulative VC raised ($m) during the measurement period of the dependent variable is included. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN Num. of patents by t+6	LN Scaled citation-weighted patents by t+6	Revenue ($ m) in t+6	Net income ($ m) in t+6	IPO	Successful Exit	LN Valuation at IPO	LN Valuation at Succ. Exit
Moves to US	0.06**	0.18***	-2.92	-0.12	-0.06***	-0.01	0.75***	0.35***
	(0.02)	(0.03)	(1.86)	(0.37)	(0.02)	(0.03)	(0.22)	(0.12)
LN VC raised ($ m) by t+6	0.10***	0.08***	4.25***	-1.23***				
	(0.01)	(0.01)	(0.51)	(0.09)				
LN VC raised ($ m) by exit					0.04***	0.04***	0.58***	0.67***
					(0.01)	(0.01)	(0.05)	(0.03)
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11066	11066	2802	2760	3813	3813	495	1225
R-squared	0.677	0.476	0.250	0.268	0.126	0.073	0.663	0.610

Table 10: Loss Tolerance: Development of Failed Startups

This table reports regression results of intermediate startup performance on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8. Panel A includes only startups that eventually failed, i.e. did not achieve an IPO or successful exit. Panel B includes all startups that eventually achieved an IPO or successful exit. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fundraising		Innovation		Commercial success	
Dependent variable:	LN VC raised ($m) by t+6	LN VC rounds by t+6	LN Num. of patents by t+6	LN Scaled citation-weighted patents by t+6	Revenue ($ m) in t+6	Net income ($ m) in t+6
Panel A: Failed Startups						
Moves to US	0.50***	0.16***	0.10***	0.20***	-1.11	-0.72*
	(0.06)	(0.02)	(0.02)	(0.03)	(1.48)	(0.37)
Observations	9824	9824	9824	9824	2771	2666
R-squared	0.726	0.093	0.709	0.474	0.180	0.162
Panel B: Successful Startups						
Moves to US	0.57***	0.19***	0.04	0.13	-5.79**	-2.01**
	(0.14)	(0.04)	(0.07)	(0.09)	(2.86)	(0.99)
Observations	1242	1242	1242	1242	631	584
R-squared	0.663	0.147	0.689	0.524	0.430	0.294
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Homogeneity Across Countries

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the US during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8. Panel A/Panel B split the sample into startups from countries with above/below median VC-to-GDP ratios, with GB, SE, IE, FI, CH having above average VC/GDP, i.e., "Leading Startup Ecosystems". Panel C/D split the sample into startups from countries with above/below average risk tolerances as measured by Falk et al. (2018), with BE, DK, IE, NL, NO, SE, and GB having above average risk tolerance. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+6	LN VC rounds by t+6	LN Num. of patents by t+6	LN Scaled citation-weighted patents by t+6	Revenue ($ m) in t+6	Net income ($ m) in t+6	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
Panel A: Leading Startup Ecosystems										
Moves to US	0.68***	0.21***	0.10***	0.22***	1.03	-1.37**	-0.00	0.02	1.55***	0.89***
	(0.08)	(0.02)	(0.03)	(0.04)	(2.85)	(0.64)	(0.01)	(0.02)	(0.42)	(0.16)
Observations	4972	4972	4972	4972	1129	1010	4972	4972	223	599
R-squared	0.688	0.117	0.663	0.453	0.234	0.130	0.038	0.047	0.545	0.411
Panel B: Lagging Startup Ecosystems										
Moves to US	0.56***	0.19***	0.14***	0.23***	-0.03	-0.76	-0.01	0.04*	1.47***	0.93***
	(0.07)	(0.02)	(0.04)	(0.05)	(2.68)	(0.54)	(0.01)	(0.02)	(0.27)	(0.22)
Observations	6094	6094	6094	6094	1673	1750	6094	6094	272	626
R-squared	0.665	0.079	0.659	0.472	0.185	0.147	0.039	0.037	0.312	0.334
Panel C: High risk-taking countries										
Moves to US	0.63***	0.20***	0.10***	0.20***	1.87	-1.54**	0.00	0.03	1.63***	1.01***
	(0.08)	(0.02)	(0.03)	(0.04)	(2.62)	(0.71)	(0.01)	(0.02)	(0.35)	(0.15)
Observations	5445	5445	5445	5445	1187	1259	5445	5445	267	688
R-squared	0.678	0.106	0.665	0.453	0.245	0.140	0.046	0.050	0.459	0.361
Panel D: Low Risk-taking countries										
Moves to US	0.59***	0.20***	0.13***	0.26***	-0.77	-0.38	-0.02**	0.02	1.00**	0.56**
	(0.08)	(0.02)	(0.05)	(0.06)	(2.43)	(0.43)	(0.01)	(0.02)	(0.38)	(0.24)
Observations	5621	5621	5621	5621	1615	1501	5621	5621	228	537
R-squared	0.672	0.083	0.657	0.474	0.175	0.135	0.032	0.031	0.353	0.390

A Internet Appendix

A.1 Merging Data Sets

A.1.1 Standardization Procedure

VentureSource is merged with several "other databases", among others, with Preqin, Orbis, SDC New Issues, SDC Mergers & Acquisitions, and the European Patent Offices' PATSTAT database. Unfortunatly, no bridge files or identifiers between these databases are available. Therefore, I match VentureSource to each of the three databases to using the following procedure, which is based on the procedure outlined in Bernstein et al. (2016). I begin by standardizing the company names in each, using the standardization routines developed by the NBER Patent Data Project[17]. These routines standardize company prefixes and suffixes (e.g., PHARMACEUTICAL(S), PHARMACEUTICA, PHARMACEUTIQUE(S), PHARMAZEUTIKA, PHARMAZEUTISCH(E)(N), and PHARMAZIE become PHARM), generating a company's "standard name" and "stem name". While the standard name does not strip any information, the "stem name" is a "core" of the company name stripping organizational form suffixes, prefixes, capital letters, punctuation, and spaces.

A.1.2 Matching Procedure

Using standard names, stem names, and countries, I employ the following matching procedure between VentureSource and each of the "other databases":

1. Each standardized company name in VentureSource (including previous ones) is matched with standardized names from the other database. If an exact match is found, this is taken to be the same company.

2. Each stem name in VentureSource is matched with stem names from the other databases. If an exact match is found and enough other identifying information matches as well, this is taken to be the same company. In particular, I consider a stem name match definite if the country and time period matches (i.e., IPO/Acquisition/first patent application was after company founding year). If an exact stem name match is found but not enough other identifying information matches as well, the match is added to a list of borderline matches to be checked manually.

3. The borderline matches, i.e. stem name matches where the country or time periods do not match or are not known, are reviewed manually using other qualitative information from both data

[17] See https://sites.google.com/site/patentdataproject/.

sources, including full company descriptions, deal summaries, and patent abstracts.

Figure A1: Moving to the U.S. and Fundraising - Matched Sample

The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The firms are tracked up to 2021. $t = 0$ is the migration year (=match year). All performance indicators are measured as average cumulative total up to year t.

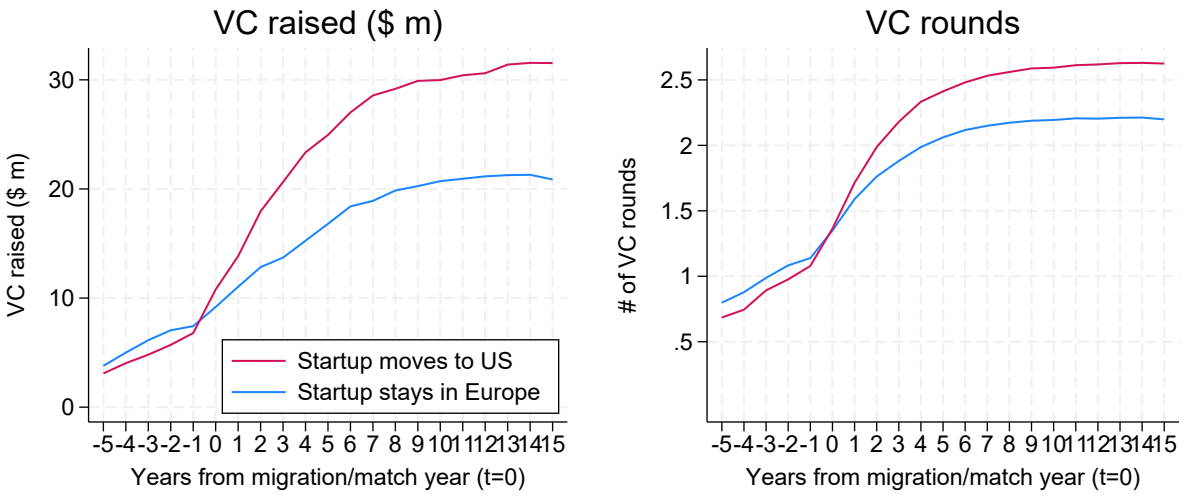


Figure A2: Moving to the U.S. and Innovation - Matched Sample

The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The firms are tracked up to 2021. $t = 0$ is the migration year (=match year). All performance indicators are measured as average cumulative total up to year t.

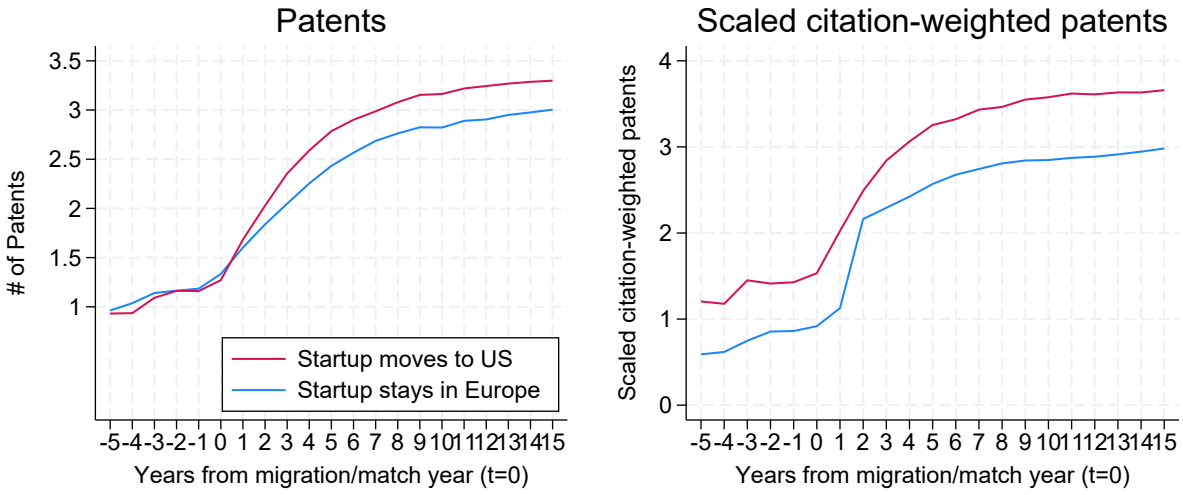


Figure A3: Moving to the U.S. and Business Success - Matched Sample

The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The firms are tracked up to 2021. $t = 0$ is the migration year (=match year). All performance indicators are measured as average in year t.

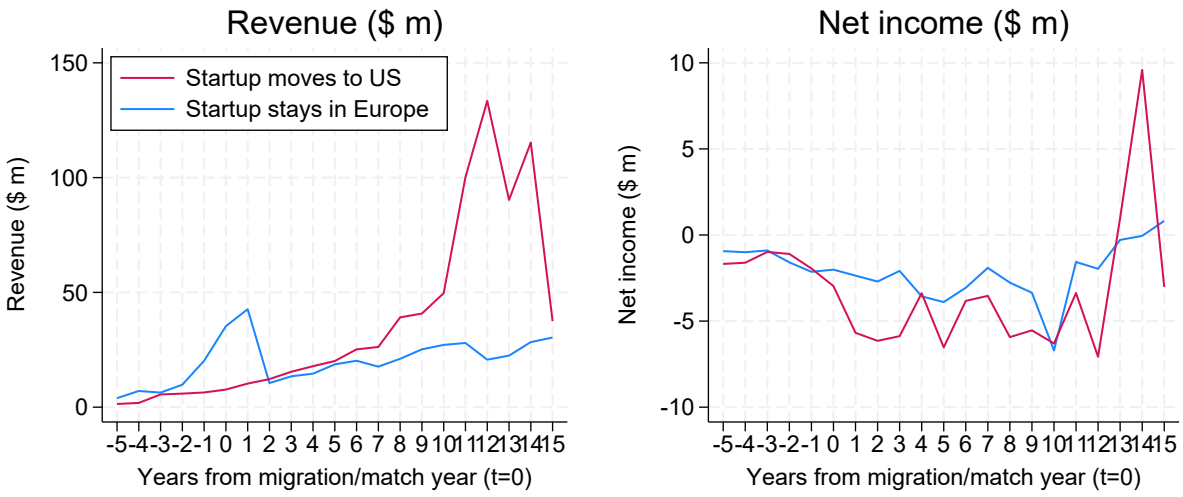


Figure A4: Moving to the U.S. and Exits - Matched Sample

The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The firms are tracked up to 2021. $t = 0$ is the migration year (=match year). All performance indicators are measured as average cumulative total up to year t.

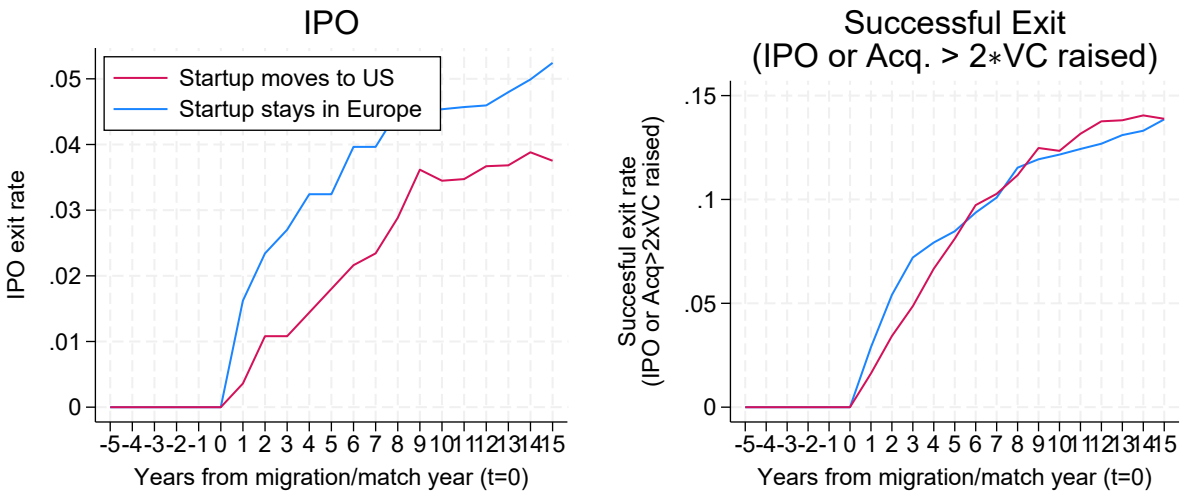


Table A1: Variable Definitions

This table contains descriptions of the variables used in the analysis.

Variable	Description
Moves to US	A dummy variable that equals one if the startup relocated ist headquarters (HQ) to the U.S.
Age at migration to US	Age of the startup at migration to the U.S.
VC raised ($ m)	VC amount raised in 2012 U.S. dollars
VC rounds	Number of (cumulative) VC rounds raised
Pre-money valuation ($ m)	Pre-money valuation at the financing in 2012 U.S. dollars
Startup age	Age of the startup
Number of VCs investing	The number of unique investors invested in the startup
US VC involved	A dummy variable that equals one if at least oneU.S. VC is invested in the startup
Revenue ($ m)	A startup's revenue in 2012 U.S. dollars
Net income ($ m)	A startup's net profit or loss in 2012 U.S. dollars
Employees	A startup's number of employees
Num. of patents	The number of (eventually granted) patents a startup has applied for
Scaled citation-weighted patents	The number of lifetime citations to patents, scaled by the average citations of all patents filed in the same country and year
Stage: Generating revenue	A dummy variable that equals one if startup already generates revenue (other stages: "Seed", "Product Development/Clinical Trial")
IPO	A dummy variable that equals one if startup goes public via initial public offering (IPO)
Valuation at IPO ($ m)	Startup valuation at IPO, i.e. first day closing price times shares outstanding, in 2012 U.S. dollars
Successful exit	A dummy variable that equals one if startup goes public via IPO or gets acquired with transaction value of > 2 times total VC raised
Valuation at Successful Exit ($ m)	Startup valuation at IPO (i.e., first day closing price times shares outstanding), or deal value at succesful acquisition, i.e. acquisition with deal value of > 2 times total VC raised, in 2012 U.S. dollars
Fixed effects	
Funding year FE	Year of first VC financing fixed effects (15 in total)
Industry FE	Startup industry fixed effects: "Software", "Hardware", "Healthcare/Biotech", "Consumer/Retail", "Other"
Stage FE	Startup stage fixed effects: "Seed", "Product Development/Clinical Trial", "Generating revenue"
Country FE	Country fixed effects for the initial headquarter location country of the startup (17 in total)

Table A2: European Coverage in Commercial VC Databases

This table shows the number of startups first funded in a given year, as captured by Refinitiv's VentureXpert (also known as Thomson One, Thomson Eikon, or Venture Economics) and Dow Jones' VentureSource (also known as VentureOne). The following filters were applied in both databases: 1) only financing rounds labeled as "VC"–excluding buyout, angel, debt, grant, and exit financings; 2) only financing rounds with round date and financing amount available; 3) Investee must not be older than 10 years in the year of the first VC financing; 4) Include companies from 17 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, and the United Kingdom.

	Number of startups first funded	
Year	VentureXpert	VentureSource
2000	1245	2236
2001	870	1074
2002	405	528
2003	349	441
2004	299	493
2005	628	528
2006	699	667
2007	511	757
2008	480	643
2009	421	569
2010	620	644
2011	648	688
2012	590	777
2013	591	898
2014	605	907
Total	8961	11850

Table A3: Firm Financials Coverage

This table shows the number of startups for which firm financials, in particular, revenue and net income, are available in the sample. Coverage is tabulated over years, starting from the year of first funding.

Years after first funding	# Startups with financial information	% of sample
0	3878	35%
1	4323	39%
2	4251	38%
3	4044	37%
4	3755	34%
5	3394	31%
6	3099	28%
7	2587	23%
8	2197	20%
9	1905	17%
10	1647	15%
11	1423	13%
12	1245	11%
13	1078	10%
14	908	8%
15	738	7%
16	622	6%
17	526	5%
Total Firm-Year Obs.	41620	

Table A4: Robustness - Early Migrants Only

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8, with the only difference that migrants that moved later than three years after first funding are dropped from the sample. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+6	LN VC rounds by t+6	LN Num. of patents by t+6	LN Scaled citation-weighted patents by t+6	Revenue ($ m) in t+6	Net income ($ m) in t+6	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
Moves to US	0.58***	0.18***	0.11***	0.22***	-3.33	-1.43*	-0.02**	0.02	1.32***	0.76***
	(0.07)	(0.02)	(0.03)	(0.04)	(3.67)	(0.84)	(0.01)	(0.02)	(0.33)	(0.20)
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10931	10931	10931	10931	2744	2704	10931	10931	485	1202
R-squared	0.677	0.094	0.662	0.462	0.169	0.115	0.049	0.045	0.458	0.378

Table A5: Robustness - Four Years After

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8, with the only difference that time-sensitive dependent variables are measured in year 4 after first funding. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+4	LN VC rounds by t+4	LN Num. of patents by t+4	LN Scaled citation-weighted patents by t+6	Revenue ($ m) in t+4	Net income ($ m) in t+4	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
Moves to US	0.52***	0.17***	0.09***	0.19***	-2.15	-0.87**	-0.01	0.03*	1.48***	0.89***
	(0.05)	(0.01)	(0.02)	(0.03)	(1.37)	(0.41)	(0.01)	(0.01)	(0.27)	(0.14)
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11066	11066	11066	11066	3402	3250	11066	11066	495	1225
R-squared	0.720	0.095	0.704	0.483	0.215	0.176	0.050	0.046	0.461	0.379

Table A6: Robustness - Eight Years After

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8, with the only difference that time-sensitive dependent variables are measured in year 8 after first funding. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+8	LN VC rounds by t+8	LN Num. of patents by t+8	LN Scaled citation-weighted patents by t+8	Revenue ($ m) in t+8	Net income ($ m) in t+8	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
Moves to US	0.68***	0.22***	0.15***	0.24***	1.96	-1.70***	-0.01	0.03*	1.48***	0.89***
	(0.06)	(0.02)	(0.03)	(0.03)	(2.84)	(0.54)	(0.01)	(0.01)	(0.27)	(0.14)
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11066	11066	11066	11066	1982	2017	11066	11066	495	1225
R-squared	0.660	0.108	0.641	0.457	0.199	0.170	0.050	0.046	0.461	0.379

Table A7: Robustness - UK Only

This table reports regression results of different startup performance measures on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The models are the same as in the Column (3)/(6) of Table 4 to Table 8, with the only difference that only startups from the UK are included. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+8	LN VC rounds by t+8	LN Num. of patents by t+8	LN Scaled citation-weighted patents by t+8	Revenue ($ m) in t+8	Net income ($ m) in t+8	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
Moves to US	0.76***	0.21***	0.10**	0.25***	0.55	-1.38	0.01	0.02	1.09***	0.92***
	(0.10)	(0.03)	(0.04)	(0.05)	(2.64)	(0.96)	(0.02)	(0.03)	(0.37)	(0.21)
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3222	3222	3222	3222	581	479	3222	3222	113	374
R-squared	0.701	0.132	0.649	0.464	0.271	0.156	0.034	0.053	0.656	0.408

Table A8: Robustness - U.S. migration or U.S. investment?

This table reports regression results of different startup performance measures on an indicator of whether the startup received U.S. VC at first funding. The unit of observation is a VC-backed startup. The samply only includes "European stayers" that did not move their HQ to the U.S. The models are similar to Column (3)/(6) of Table 4 to Table 8, with the difference that U.S. VC involvement is the variable of interest. All variables are defined in Appendix A1. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fundraising		Innovation		Commercial success		Exit		Valuation at exit	
Dependent variable:	LN VC raised ($m) by t+8	LN VC rounds by t+8	LN Num. of patents by t+8	LN Scaled citation-weighted patents by t+8	Revenue ($ m) in t+8	Net income ($ m) in t+8	IPO	Successful Exit	LN Valuation at IPO ($)	LN Valuation at Successful Exit ($)
US VC in first round	0.19***	0.04***	0.03	0.03	5.58**	-0.19	0.02*	0.03*	0.07	0.16
	(0.04)	(0.01)	(0.02)	(0.02)	(2.38)	(0.37)	(0.01)	(0.01)	(0.15)	(0.13)
Observations	10511	10511	10511	10511	2620	2574	10511	10511	473	1144
R-squared	0.682	0.082	0.668	0.463	0.217	0.162	0.050	0.045	0.442	0.368
First funding controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A9: Matching - Characteristics of Treatment and Control Firms

This table provides mean comparisons between startups moving their headquarters (HQ) to the U.S. and a matched sample of staying startups. Startup characteristics are measured in the match year (=migration year). The control group is identified based on exact matching on industry, migration year, and stage, and then using the nearest neighbor based Mahalanobis distance matching. Distance is calculated based on the cumulative VC amount raised, cumulative number of rounds, age, number of VCs invested, an indicator of whether a U.S. VC is invested, and an indicator of whether the startup has at least one patent. All variables are defined in Appendix A1. The last column reports t-statistics of two-sample t-tests for equality of means. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Stays in Europe	Moves to US	Difference		
	Mean	Mean	Mean	t-stat.	
Panel A: Startup characteristics in match/migration year (t=0)					
VC raised ($ m)	9.19	10.79	1.60	1.33	
VC rounds	1.35	1.36	0.01	0.21	
Startup age	4.19	4.17	-0.02	-0.08	
Num. of unique VCs invested	2.46	2.53	0.07	0.48	
US VC involved	0.32	0.32	0.00	0.00	
Revenue ($ m)	35.30	7.67	-27.63	-1.10	
Net income ($ m)	-2.01	-2.96	-0.95	-1.40	
Num. of patents	1.33	1.27	-0.06	-0.27	
Stage					
Pre-funding	0.21	0.21	0.00	0.00	
Seed	0.05	0.05	0.00	0.14	
Product Development/Clinical Trial	0.17	0.17	0.00	-0.08	
Generating Revenue	0.58	0.58	0.00	0.00	
Industry					
Software	0.38	0.38	0.00	0.00	
Hardware	0.11	0.11	0.00	0.00	
Medical/Biotechnology	0.12	0.12	0.00	0.00	
Consumer/Retail	0.14	0.14	0.00	0.00	
Other Industry	0.25	0.25	0.00	0.00	
Country					
France	0.17	0.17	0.00	0.08	
Germany	0.11	0.09	-0.02	-1.21	
Sweden	0.05	0.05	0.00	-0.27	
United Kingdom	0.34	0.31	-0.03	-1.16	
Other Country	0.33	0.39	0.06	1.94	*
Panel B: Startup performance variables					
VC raised ($ m) by t+6	18.40	27.01	8.61	3.30***	
VC rounds by t+6	2.12	2.48	0.36	4.22***	
Num. of patents by t+6	2.57	2.90	0.34	0.75	
Scaled citation-weighted patents by t+6	2.68	3.32	0.65	0.60	
Revenue ($ m) in t+6	20.22	25.19	4.97	0.57	
Net income ($ m) in t+6	-3.06	-3.83	-0.76	-0.44	
IPO	0.05	0.04	-0.01	-1.00	
Successful Exit (IPO or Acq. ¿ 2*VC raised)	0.14	0.15	0.01	0.43	
Observations	555	555	1110		

Table A10: Moving to the U.S. and Fundraising - Matched Sample

This table reports regression results of startup fundraising performance on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The dependent variable is the cumulative VC raised (in $ m) by year 6 after migration/match in Columns (1)-(3), and cumulative number of VC rounds in Columns (4)-(6). $t = 0$ is the migration/match year. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	LN VC raised ($ m) by $t+6$			LN VC rounds by $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	0.68***	0.74***	0.58***	0.12***	0.12***	0.11***
	(0.13)	(0.12)	(0.07)	(0.03)	(0.03)	(0.02)
LN VC raised ($ m) by t=0			0.01			-0.01***
			(0.01)			(0.00)
LN Startup age in t=0			-0.27***			-0.01
			(0.10)			(0.01)
LN Num. of unique VCs invested by t=0			0.57***			0.31***
			(0.11)			(0.03)
US VC involved by t=0			0.86***			0.11***
			(0.11)			(0.03)
LN Num. of patents granted by t=0			0.28***			0.04**
			(0.06)			(0.02)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	No	Yes	No	No	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	1110	1110	1110	1110	1110	1110
R-squared	0.025	0.111	0.594	0.020	0.119	0.441

Table A11: Moving to the U.S. and Innovation - Matched Sample

This table reports regression results of startup innovation performance on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The dependent variable is the cumulative number of patents granted by year 6 after migration/match in Columns (1)-(3), and cumulative scaled citation-weighted patents in Columns (4)-(6). $t = 0$ is the migration/match year. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	LN Num. of patents by $t+6$			LN Scaled citation-weighted patents by $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	0.09	0.08	0.10***	0.19***	0.18***	0.20***
	(0.06)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)
LN VC raised ($ m) by t=0			-0.00			-0.01
			(0.00)			(0.01)
LN Startup age in t=0			-0.13***			-0.11***
			(0.03)			(0.03)
LN Num. of unique VCs invested by t=0			0.04			0.08
			(0.05)			(0.06)
US VC involved by t=0			0.06			0.03
			(0.04)			(0.05)
LN Num. of patents granted by t=0			1.05***			0.91***
			(0.03)			(0.04)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	No	Yes	No	No	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	1110	1110	1110	1110	1110	1110
R-squared	0.002	0.229	0.756	0.010	0.168	0.582

Table A12: Moving to the U.S. and Commercial Success - Matched Sample

This table reports regression results of startup commercial success on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The dependent variable is the revenue in year 6 after migration/match in Columns (1)-(3), and net income in Columns (4)-(6). $t = 0$ is the migration/match year. Revenue and net income are winsorized at the 1% and 99% ends. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Revenue ($ m) in $t+6$			Net income ($ m) in $t+6$		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	5.77	4.26	3.60	-0.39	0.15	0.39
	(3.52)	(3.42)	(3.24)	(0.69)	(0.81)	(0.81)
LN VC raised ($ m) by t=0			1.07*			0.14
			(0.63)			(0.09)
LN Startup age in t=0			5.01*			-0.18
			(2.54)			(0.44)
LN Num. of unique VCs invested by t=0			-9.81			-3.01***
			(6.64)			(1.07)
US VC involved by t=0			14.11**			0.63
			(5.78)			(0.96)
LN Num. of patents granted by t=0			-2.63			-0.28
			(2.23)			(0.42)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	No	Yes	No	No	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	270	270	270	268	268	268
R-squared	0.014	0.201	0.308	0.001	0.278	0.354

Table A13: Moving to the U.S. and Exits - Matched Sample

This table reports regression results of startup exit outcomes on an indicator of whether the startup moved to the U.S. during the VC funding period. The unit of observation is a VC-backed startup. The sample consists of the treatment and control samples resulting from the matching procedure described in the body of the text. The dependent variables are dummy variables indicating whether the startup had an exit via IPO in Columns (1)-(3)/IPO or successful acquisition (i.e., acquisition with valuation larger than $2 * VC_raised$) in Columns (4)-(6), by the end of the sample period (July 2021). $t = 0$ is the migration/match year. LN denotes the natural logarithm of a variable incremented by one. All models are estimated using ordinary-least-squares (OLS). Standard errors clustered at the industry x year level are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	IPO			Successful Exit (IPO or Acq>2*VC raised)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moves to US	-0.01	-0.01	-0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
LN VC raised ($ m) by t=0			-0.00			-0.00
			(0.00)			(0.00)
LN Startup age in t=0			-0.00			-0.04**
			(0.01)			(0.02)
LN Num. of unique VCs invested by t=0			0.01			0.03
			(0.02)			(0.03)
US VC involved by t=0			0.06***			0.07**
			(0.02)			(0.03)
LN Num. of patents granted by t=0			-0.00			0.00
			(0.01)			(0.02)
Funding Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Stage FE	No	No	Yes	No	No	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	1110	1110	1110	1110	1110	1110
R-squared	0.001	0.077	0.098	0.000	0.060	0.081